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The Impacts of Climate Change on groundwater recharge in low storativity fractured bedrock aquifers

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Declaration

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Summary

As the largest store of available fresh water on the planet, groundwater is a priceless resource that needs to be preserved. However, because of ongoing climate change the resilience of the groundwater resources is at stake. Whilst climate change projections are highly uncertain, there is wide agreement on: (i) an intensification of the hydrological cycle is anticipated, and (ii) local and regional geological characteristics have a strong control on the magnitude of the possible impacts of a changing climate.

The hydrogeology of Ireland is characterized by fractured bedrock aquifers with low storativity, which are often overlain by low permeability glacial tills. These two features are known to constrain the volume of water reaching the aquifer that becomes actual recharge. As a first approach in this doctoral research, a sensitivity analysis was carried out to examine the controls exerted by the meteorological and hydrogeological variables. The results show that the hydrogeological settings – and especially the aquifer storage capacity - have a larger control on local recharge than the meteorological factors.

A recharge characterisation exercise was carried out in two main study catchments to evaluate the storage capacity of the underlying aquifers. The study catchments selected for this and other research activities described below were the Dripsey in Co Cork and the Mattock in Co Meath/Louth (two catchments of contrasting hydrogeology, where a reasonable amount of data was available). A range of recharge calculation methods were applied to constrain recharge uncertainty and use it as a proxy to assess the aquifer specific yield. The results obtained through the water table fluctuation method demonstrated the limited storage capacity of the aquifers; in wet periods the groundwater levels often present a “*roof effect*” as they reach a maximum level that is not exceeded. This behaviour indicates that the aquifer is unable to accept further recharge, which is confirmed by low groundwater recharge estimations in relation to the accumulated rainfall.

Furthermore, the sensitivity analysis also showed that the recharge coefficients (and hence the infiltration processes through the vadose zone), govern groundwater recharge as long as the underlying aquifer does not have limited storage capacity. To better understand the effect of the overlying soils and subsoils, the infiltration capacity of two additional study sites was modelled through the implementation of Hydrus 1D in both sites.

Once it had been established how the bedrock properties control groundwater recharge, the relationship between the main meteorological variables and groundwater levels was analysed through the application of Continuous Wavelet Transforms (CWTs) and Wavelet Coherence (WTC). The results show that the linearity of the rainfall-groundwater levels relationship is strongly dependent on the physical characteristics of the groundwater system, as the presence of a well-developed transition zone can *buffer* the recharge signal to the shallow bedrock below. Moreover, to better understand the effects of the current climate variability on groundwater levels, the WTC was also applied to examine the connection between large-scale circulation patterns and the groundwater levels. The results demonstrated that these patterns have a clear influence at annual and multiannual scales, but also at a seasonal scale in the cases where the index has a clear seasonal fingerprint.

To be able to represent the characteristic Irish hydrogeological features described above under future climate scenarios, an approach combining Maximum Overlap Discrete Wavelet Transforms (MODWT) and Nonlinear autoregressive networks with exogenous inputs (NARX) was applied to forecast monthly groundwater levels up to one year for the two main study catchments. The input variables are decomposed into details, that are then aggregated according to different criteria to find a best-performing model. The trained WT-NARX models achieved good performances and have shown that the decomposition of the input variables improves the performance of the model as long as overfitting does not occur.

The NAM rainfall-runoff model was used, in conjunction with climate projections, to generate baseflow simulations up to the year 2100. Additionally, the WT-NARX models were also forced with the averaged climate conditions represented by the climate projections but also by synthetic rainfall series to simulate enhanced rainfall occurrence and seasonality. In this way, the NAM provided a long-term simulation of the possible impacts whereas the WT-NARX approach proved useful for short-term forecasts and stress-testing of the system, i.e., for the identification of critical values that could lead to a critical depletion of the groundwater levels.

This PhD dissertation presents an integrated approach for investigating the possible impacts of climate change on Irish bedrock aquifers. The methodology applied differs from more classical impact assessments by analysing thoroughly the interactions of bedrock properties, climate and

groundwater levels. As a result, a novel approach to stress-test the groundwater levels is proposed, which could potentially be applied to any region and aquifer type. The outcomes provide a baseline for further impact assessments and could be used to inform water management strategies.

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Abbreviations and Symbols

AE	Actual Evapotranspiration
AMO	Atlantic Multidecadal Oscillation
ANN	Artificial Neural Networks
BFI	Baseflow Index
COI	Cone of Influence
CWT	Continuous Wavelet Transform
DR	Dripsey
DWT	Discrete Wavelet Transform
DWTF	Double Water Table Fluctuation
EA	East Atlantic Pattern
EPA	Environmental Protection Agency
ESB	Electricity Supply Board
ET	Evapotranspiration
FAO	Food and Agriculture Organisation
GBI	Greenland Blocking Index
GCMs	General Circulation Models
GIS	Geographic Information Systems
GSI	Geological Survey of Ireland
GWL	Groundwater Levels
IPCC	Intergovernmental Panel on Climate Change
IWGGW	Irish Working Group on Groundwater
KGE	Kling-Gupta efficiency
mbgl	meters below ground level
MK	Mattock
mOD	Meters above OrdnanceDatum
MODWT	Maximum Overlap Discrete Wavelet Transform
MPL	multi-layer-perceptron
MRA	Multiresolution Analysis
NAO	North Atlantic Oscillation
NARX	Nonlinear autoregressive networks with exogenous inputs
NSE	Nash-Sutcliffe efficiency
PCA	Principal Component Analysis
PE	Potential Evapotranspiration
PI, Pu, LI	Poorly productive aquifer
PPAs	Poorly Productive Aquifers
Qobs	Observed river discharge
Qsim	Simulated river discharge
RCMs	Regional Climate Models

SCA	Scandinavian Pattern
SDSM-DC	Statistical Downscaling Model-Decision Centric
SERES	fourth IPCC report on Emission Scenarios
Sy	Specific Yield
Tmax	Maximum Temperature
Tmean	Mean Temperature
Tmin	Minimum Temperature
TZ	Transition Zone
WFD	Water Framework Directive
WT	Wavelet Transforms
WT ANN	Wavelet Transforms- Artificial Neural Networks
WTC	Wavelet Coherence
WTF	Water Table Fluctuation

1. Introduction

1.1. Background and Overview

As the largest store of available fresh water at global scale, groundwater is a valuable resource that must be preserved. Groundwater plays a key role as a water supply for population, as it supplies 50% of drinking water, over 40% of the world's irrigation water, and it is increasingly important as a source of energy. Moreover, it also has a crucial role in nourishing river base flows, and ecosystems. Accurate estimates of groundwater recharge are essential in order to quantify and manage groundwater resources, understand the contribution of groundwater to rivers and dependent ecosystems and to delineate source protection zones around wells and springs among other issues. In Ireland, most of the public water supplies come from surface water and approximately 15 % come from groundwater resources with this proportion increasing in rural areas (Williams and Lee 2010). Until recently (i.e. Falzoi et al. 2019), most Irish aquifers had generally never been considered to be under stress from a quantitative point of view (Moe et al. 2007), so groundwater recharge mechanisms and their quantification had received little attention. Therefore, the characterization and identification of the properties controlling groundwater recharge in the Irish context (geology and climate) had been poorly studied. In the 2000's, after the implementation of the European Water Framework Directive (WFD), several studies focused on investigating and quantifying groundwater resources at local and national scale. The research effort focused on data collection at the national scale to constrain the main parameters known to affect and control groundwater recharge such as permeability; subsoil thickness; aquifer storage capacity; and the presence of karst features. As a result, a GIS-based methodology was developed for estimating recharge, the main outcome being the National Recharge Map (Misstear et al. 2009a; Hunter Williams et al. 2013).

In addition, in the context of a changing climate, changes in precipitation distribution, amounts and intensity are anticipated. Whilst climate change projections are highly uncertain, there is wide agreement in the prediction of an intensification of the hydrological cycle, making the water resources vulnerable to climate change (Bates et al. 2008), which could affect groundwater resources directly by changing recharge rates, and indirectly by changing the use of the groundwater resources (Taylor et al. 2013). This alteration of the hydrological cycle points at possible reductions in groundwater recharge in Ireland (Sweeney et al., 2008; Gleeson et al.,

2013). The effect of all these processes needs to be accounted for in groundwater recharge predictions to provide estimates of the water resources in the future.

In Ireland, approximately 65% of the aquifers are regarded as poorly productive (PPAs)(Williams and Lee 2010). Hence, an important element of research within this project was to determine how bedrock characteristics of these aquifers govern groundwater recharge within the Irish context, where the presence of low permeability glacial tills, and aquifers with a restricted storage capacity are abundant, and known to have a large influence on recharge processes (Scanlon et al. 2002; Fitzsimons and Missteart 2006; Hunter Williams et al. 2013). Additionally, a detailed understanding of the conceptual model of river catchments and aquifer systems is necessary to be able to generate more accurate climate change impact assessments. For this reason, a significant part of this project has been focused on modelling recharge processes and groundwater levels in PPAs to then simulate the possible impacts of climate change by generating future recharge scenarios in two study catchments. The reader should note that, throughout this manuscript, groundwater recharge is understood as the downward vertical flow resulting from rainfall infiltration and percolation that reaches the water table and contributes to the long-term groundwater resources of the underlying aquifer. A fuller definition is provided in Section 2.1.

These study catchments, the Mattock in Co. Meath and the Dripsey in Co. Cork., were selected as they represent the main features of PPAs within the Irish context but, at the same time, present contrasting hydrogeological and climatic characteristics. Furthermore, additional study catchments and/or sites have been included for specific chapters when a comparison would clarify the interpretation of the results, or when no data was available for the selected catchments.

Moreover, extreme events are anticipated to occur more frequently as a consequence of climate change. Therefore, it is crucial to understand the relationship between the main meteorological variables (i.e. rainfall and temperature) and groundwater level fluctuations. A significant percentage of the low-frequency climate variability occurring within Ireland can be explained by large-scale circulation patterns such as the Atlantic Multidecadal Oscillation (AMO) (Knight et al. 2006), and North Atlantic Oscillation (NAO) (Comas-Bru and Mcdermott 2014). Furthermore, several authors have pointed out that Global Circulation Models (GCMs) and Regional Circulation Models (RCMs), which are the main tools in climate change impact

assessments, fail to fully reproduce some of these patterns or some characteristics (i.e. cyclicity) of other patterns (e.g. Stephenson et al. 2006; Furtado et al. 2011; Lapp et al. 2012). Therefore, there is the need to evaluate the control that large-scale patterns exert on Irish groundwater resources, as the understanding of this linkage is vital for better water management under a changing climate.

The integrated approach of this thesis to assessing the impacts of climate change on Irish bedrock aquifers will set a baseline for future impact assessments that could be used to inform water management strategies.

1.2. Research Questions, Objectives and Approach

The overall purpose of this research project is to evaluate future groundwater recharge in Ireland under a changing climate. In other words, future recharge scenarios will be generated, and their consequences examined through subsequent climate and hydrological modelling. More specifically, the thesis is focused on answering the following key questions:

1. How do bedrock properties affect the response of the aquifer to present and future recharge?
2. How would climate change impact on Irish regional groundwater resources?

These objectives have been achieved by:

1. Using the national recharge map, which is based on the recharge coefficients approach (Hunter Williams et al. 2013), to carry out a sensitivity analysis of recharge estimates based on changes to hydrometeorological and hydrogeological variables. The aim of this analysis is to identify which variables exert the most significant influence on groundwater recharge at annual scale, but also to have a rough quantification of the impact on recharge when modifying these variables.
2. Investigation of the infiltration processes through the unsaturated zone by: (i) examining the differences between different Potential Evapotranspiration estimation methods and (ii) carrying out 1-D modelling of the unsaturated zone with Hydrus 1D for two additional study sites.

3. Application of a total of six recharge estimation methods and three complementary methods in order to approximate an effective storage capacity for the study catchments and improve our understanding on the recharge processes within the study areas.
4. Analysis of the cyclicity and climate patterns in rainfall, temperature and groundwater levels by applying Continuous Wavelet Transforms (CWTs) and Wavelet Transform Coherence (WTC). The low-frequency variability observed in the meteorological variables can be linked to large atmospheric patterns such as the North Atlantic Oscillation (NAO), the Atlantic Multidecadal Oscillation (AMO), and the East Atlantic Pattern (EA). Finally, the WTC is applied to: (i) Unveil the relationship between the climate variables (rainfall and temperature) with the groundwater level and (ii) Assess how the large-scale circulation patterns affect the availability of groundwater resources.
5. Development and implementation of a model coupling Wavelet Transforms and Artificial Neural Networks in order to forecast monthly groundwater levels up to one year ahead. This is a data-driven model which includes indirectly the subsoil and bedrock properties of the studied fractured aquifers. Hence, these properties can be accounted for when changing the meteorological inputs to simulate the possible effects of climate change.
6. Assessment of the groundwater recharge sensitivity of the study areas to climate variability by forcing the WT-ANN model, with synthetic rainfall and temperature time-series. This is a novel approach in climate change impact assessment, as WT-ANN have not been applied in this way before. Additionally, the forcing of the model with synthetic weather time-series allows the identification of threshold values for the system.
7. Long-term assessment of the possible impacts of Climate Change on groundwater recharge by forcing the NAM rainfall-runoff model (Nielsen and Hansen 1973) with climate projections. The outputs are analysed taking into consideration the results obtained by the recharge characterisation and so, including the hydrogeological characteristics of the catchments.

This PhD dissertation aims to provide contribution to science both at Irish and international level by (i) improving the understanding of local and regional hydrogeological features and their interaction with climate and climate variability and (ii) implementing and testing novel approaches for groundwater resources studies and climate change impact assessments. Further description of the novelty of this thesis, and overall contributions to science from this research project are presented in Chapter 10.

1.3. Scope and Thesis Layout

The overall scope of this thesis is represented in Figure 1.1 and it's laid out as follows:

- Review of the available literature research of Irish hydrogeology, hydrogeology of fractured aquifers and climate change impact assessments on groundwater resources (Chapter 2). A specific literature review for each topic is then presented at the beginning of each corresponding chapter.
- Description of the general methodology followed during the project and presentation of the study areas, their hydrogeological characteristics, soils, subsoils and land-use settings. (Chapter 3).
- Application of the national recharge map and sensitivity analysis of annual groundwater recharge to selected study areas. This analysis covers a generic approach at county scale and a more specific procedure at catchment scale with further discussion of results (Chapter 4).
- Evaluation of the uncertainty associated with the monthly potential evapotranspiration estimation techniques within the selected study catchments. Modelling of the infiltration processes through the unsaturated zone in two additional study sites, and estimation of the infiltration capacity at hourly and daily resolution with discussion of results (Chapter 5).
- Application of a range of recharge estimation methods to the two main study catchments (i.e Mattock and Dripsey) to evaluate the recharge acceptance capacity of these aquifers at monthly and annual scale, and further discussion of results and implications (Chapter 6).
- Application of Continuous Wavelet Transforms (CWT) to examine the annual and multiannual cyclicity and stationarity of the climate within the study areas and its link with the groundwater table dynamics at daily resolution. Analysis of the influence of large-scale atmospheric and oceanic circulation patterns on low-frequency groundwater level variability with additional discussion of results (Chapter 7).
- Development and application of a methodology to forecast monthly groundwater levels by coupling of Wavelet Transforms (WT) and Artificial Neural Networks (ANN) and further discussion of the results (Chapter 8).
- Climate Change impact assessment over the study catchments. Two different approaches are presented: (1) a classical approach forcing the NAM rainfall-runoff model with climate projections, which produces monthly and annual recharge

estimations until 2100, and (2) a novel approach using the ANN model presented in the previous chapter that forecasts groundwater levels up to one year at monthly resolution. Additional discussion of the results and implications (Chapter 9).

- General discussion, conclusions and recommendations (Chapter 10). In this final chapter the main findings and contributions to science are summarised and discussed as well as the applicability of the novel approaches applied through the research project.

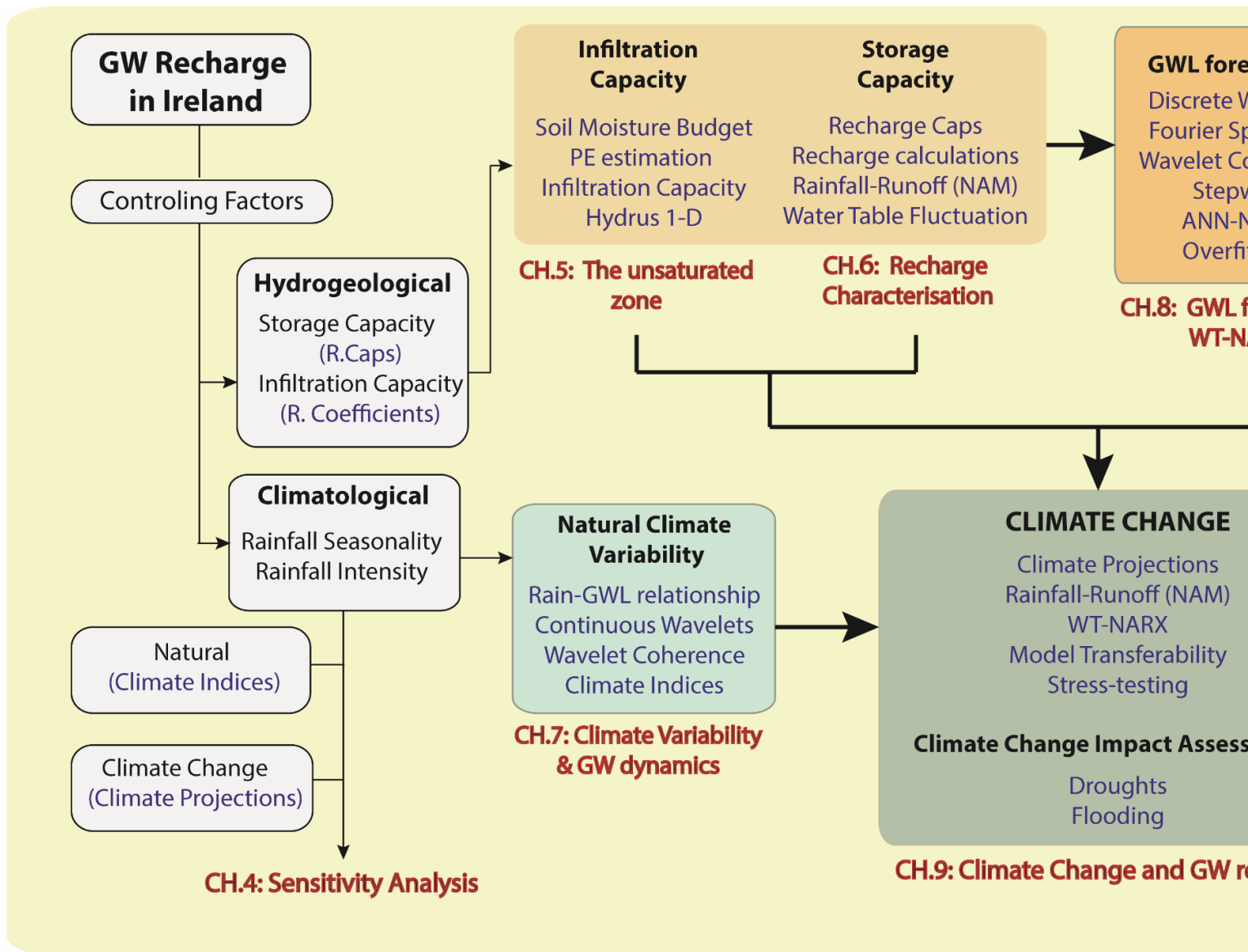


Figure 1.1: Flow chart of the thesis content and its layout.

2. General literature review

2.1 Groundwater recharge

Groundwater recharge can be defined as the ‘the downward flow of water reaching the water table, forming an addition to the groundwater reservoir’ (Lerner et al. 1990). It can originate from the infiltration of precipitation or irrigation through the unsaturated zone into the water table (*diffuse or direct recharge*), or by infiltration of water through preferential pathways such as lakes, streams, fractures or swallow holes (*localized, point or indirect recharge*). Finally, recharge can also take place by lateral flow from one groundwater body to another.

Recharge estimations are an essential element of water balance calculations at all scales, and critical for water-resources assessments and management, as well as vulnerability studies. In other words, groundwater recharge information is indispensable for any research in hydrogeology. However, it is almost impossible to have direct measurements of recharge, so it has to be approximated using calculation methods (Risser et al. 2005). Due to the intrinsic uncertainty of groundwater recharge calculations, it is strongly advised that multiple techniques are used to provide estimates and the results compared (Healy 2010).

The selection of the methods to use has a number of implications, and several factors must be taken into account. Hence, even though the choice of the methodology is influenced by the available data, the conceptual model of the flow system must be taken into consideration, as well as the accuracy required for the purpose of the study. Several authors have addressed the issue of the technique selection; for example Scanlon et al. (2002) examine a number of recharge quantification methods, along with their applicability in terms of temporal and spatial resolution. The factors to consider when choosing methods are identified, and the importance of climate is highlighted as it determines recharge rates and sources. Nevertheless, it is common to choose the recharge estimation method according to data availability rather than on the conceptual model or their resolution. Due to the inherent uncertainty associated with groundwater recharge estimations, the transgression of the method’s assumptions is often only evidenced when comparing the results with other methods (Walker et al. 2019). For all of these reasons, it is a common practice to compare several recharge estimation methods. For example, Healy and Cook (2002) investigate different methods to quantify recharge but, in this case, the study is focused just on the techniques based on the analysis of groundwater levels, providing

examples for each method and comparing them. Other authors such as Risser et al. (2005) have put it all into practice by choosing a number of methods and applying them to a specific area, to then compare the results obtained. In addition, because each method assesses different types of recharge, the range of results can provide further insights on the conceptual model (Coes et al. 2007; King et al. 2017; Walker et al. 2019).

2.1.1 Irish Hydrogeology

Until recently, groundwater resources in Ireland had never been considered to be under stress from a quantitative point of view; in fact, an assessment of abstraction pressures conducted by Moe et al. (2007) showed that - at that time - less than 1% of the groundwater bodies in Ireland were at risk of over-abstraction and less than 5% potentially at risk. Nevertheless, in recent years exceptionally dry periods such as the summer of 2018, lead to hydro(geo)logical droughts (Falzoi et al. 2019) and have tested the resilience of the groundwater resources under pressure.

In this context, it does not come as a surprise that the main research efforts in the 1970s to 1990s were focused on other issues such as groundwater vulnerability, pollution risk and groundwater protection. In 2000, the European Water Framework Directive (2000/60/EEC) was introduced which, together with a growing awareness about the importance of groundwater resources for sustaining ecosystems, generated interest in exploring the quantitative aspects of groundwater in Ireland. More specifically, a greater emphasis has been placed on studying groundwater recharge mechanisms and influencing factors.

In humid regions like Ireland, aquifers are often full, and shallow groundwater or interflow is discharged into streams. In this climatic context, recharge rates are limited by the aquifer's storage capacity, which is strongly affected by the subsurface geology (Scanlon et al. 2002). Therefore, groundwater recharge is mainly governed by the hydrologically effective rainfall - defined as the difference between total rainfall and actual evapotranspiration (Hulme et al. 2001) - and thus, the volume of available water that can potentially reach the water table. The amount of recharge is also determined by subsoil characteristics such as thickness and permeability which can control the water quantity going through the soil, i.e. potential recharge (Hulme et al. 2001). Eventually, the aquifer storage capacity limits the percentage of potential recharge becoming actual recharge (Hunter Williams and Lee 2010). Both the control exerted by subsoil characteristics and the aquifer storage capacity, are especially relevant in the Irish context because (i) a significant part of the island is covered by glacial deposits, generally

between 5-15 m in thickness (Fitzsimons and Missteart 2006), and (ii) the bedrock geology of Ireland comprises Precambrian to Upper Palaeozoic igneous, metamorphic and sedimentary rocks. These lithologies are characterized by having a negligible primary porosity, resulting in water flow occurring mainly through fissures and fractures. Because of these geological settings, approximately two-thirds of the country is underlain by hard-rock aquifers regarded as Poorly Productive Aquifers (PPAs) (Hunter Williams and Lee 2010), according to the GSI aquifer classification. According to this classification, Irish aquifers are regarded as poorly productive if they correspond to the LI, Pu or PI aquifer classes, as indicated in the table below.

Because of the combination of low permeability subsoils and restricted aquifer storage capacity, recharge estimations in Ireland have been traditionally based on a combination of soil moisture budgeting, with the implementation of infiltration or recharge coefficients, which represent the percentage of effective rainfall becoming actual recharge. The first to implement this approach in Ireland were Wright and Fried (1982) who proposed a set of infiltration coefficients. Afterwards, Daly (1994) produced another set of coefficients while studying the Nore catchment. Finally, during the 2000's research efforts were focused on recharge estimations, and a number of studies were carried out to characterise recharge mechanisms and rates in different hydrogeological settings around the country.

Fitzsimons and Missteart (2006) studied the influence of glacial till properties on recharge using a one-dimensional numerical model with a sensitivity analysis, which included the soil moisture budgeting parameters and the till properties. The results show that the till thickness and especially permeability have a greater influence on recharge than the budgeting parameters. In fact, permeability is the parameter which has the greatest influence since it can vary by several orders of magnitude. Therefore, till characteristics control vertical hydraulic gradients and infiltration rates. The authors also highlight the danger of limiting recharge estimations to soil moisture budgeting methods and the importance of understanding the influence of bedrock geology on recharge.

In another study, Missteart et al. (2008) investigated groundwater recharge in the Knockatallon aquifer in County Monaghan, which is regarded as 'locally important' and has significant abstraction for local water supply. The main aim of the study was to quantify the linkage between groundwater recharge and groundwater vulnerability, and it confirmed the results obtained in the previous study, showing low recharge rates where the till cover is thick and has low permeability. Missteart et al. (2009b) applied several methods to estimate groundwater

recharge in a major sand and gravel aquifer in County Kildare. As a result, a range of likely recharge coefficients range was established. In all of these research projects several methods were used to quantify groundwater recharge and recalculate the recharge coefficient values which were compared with the previous studies carried out in Ireland.

Groundwater vulnerability is defined by the Geological Survey of Ireland (GSI) as “a term used to represent the intrinsic geological and hydrogeological characteristics that determine the ease with which groundwater may be contaminated by human activities” (DELG/EPA/GSI 1999). Some of the factors controlling aquifer vulnerability include the infiltration characteristics of the topsoil, the permeability and thickness of the subsoil, the thickness and properties of the unsaturated zone, the type of aquifer and the amount and nature of groundwater recharge. From these parameters, the land surface can be classified into four vulnerability categories depending on the hydrogeological settings of each specific location (Table 2.1).

Table 2.1: Vulnerability mapping guidelines. Modified from: Groundwater Protection Schemes document (DELG/EPA/GSI, 1999)

Settings	Subsoil Permeability (type) and Thickness			Unsaturated Zone	Karst Features
Vulnerability Rating	High Permeability (sand/gravel)	Moderate Permeability (sandy subsoil)	Low Permeability (clay, peat)	Sand/Gravel Aquifers Only	(<30m radius)
Extreme (X)	0-1	0-1	0-1	0-1	0-1
Extreme (E)	1 - 3m	1 - 3m	1 - 3m	1 - 3m	-
High (H)	> 3m	3 - 10m	3 - 5m	> 3m	N/A
Moderate (M)	N/A	>10m	5 - 10m	N/A	N/A
Low (L)	N/A	N/A	>10m	N/A	N/A

As Misstear et al. (2009a) suggested, groundwater vulnerability and recharge are closely related since both depend on the infiltration rates through the unsaturated zone to the water table. In fact, recharge rates and their mechanisms are one of the criteria considered when determining the vulnerability category. The main objective of that study was to quantify the linkage between groundwater recharge and vulnerability. This was achieved by coupling the recharge coefficients mentioned above with the vulnerability categories to obtain a methodology to calculate first estimations of recharge. Further research on this linkage between vulnerability, combined with

previous studies (Swartz et al. 2013), lead to the development of a methodology for quantifying recharge using geological and hydrological information contained in a GIS tool. First, the hydrologically effective rainfall is calculated using a soil moisture budget approach. Then a recharge coefficient is applied which determines the proportion of the effective rainfall that forms potential recharge (Table 2.2). The main factors influencing the recharge coefficient are the permeability and thickness of the subsoils; the drainage characteristics of the soils; the presence of peat deposits; and the presence of karst features. The potential recharge is then adjusted by taking into account the ability of the aquifer to accept the recharge. Thus, for aquifers regarded as poorly productive, the corresponding recharge caps are applied (Figure 2.1): 100 mm/y for aquifers within the Pl and Pu categories, and 200 mm/y if they are classified as Ll.

Table 2.2: Recharge coefficients for different hydrogeological settings. Extracted from Hunter Williams et al. (2013).

Groundwater vulnerability category	Hydrogeological setting	Recharge coefficient (RC)		
		Minimum (%)	Inner range (%)	Maximum (%)
<i>Extreme</i> (X or E)	1.i Areas where rock is at ground surface	30	80–90	100
	1.ii Sand or gravel overlain by ‘well-drained’ soil	50	80–90	100
	1.iii Sand or gravel overlain by ‘poorly drained’ (gley) soil	15	35–50	70
	1.iv Till overlain by ‘well-drained’ soil	45	50–70	80
	1.v Till overlain by ‘poorly drained’ (gley) soil	5	15–30	50
	1.vi Sand or gravel aquifer where the water table is ≤ 3 m below surface	50	80–90	100
	1.vii Peat	1	15–30	50
<i>High</i> (H)	2.i Sand or gravel aquifer, overlain by ‘well-drained’ soil	50	80–90	100
	2.ii High permeability subsoil (sand or gravel) overlain by ‘well-drained’ soil	50	80–90	100
	2.iii High permeability subsoil (sand or gravel) overlain by ‘poorly drained’ soil	15	35–50	70
	2.iv Sand or gravel aquifer, overlain by ‘poorly drained’ soil	15	35–50	70
	2.v Moderate permeability subsoil overlain by ‘well-drained’ soil	35	50–70	80
	2.vi Moderate permeability subsoil overlain by ‘poorly drained’ (gley) soil	10	15–30	50
	2.vii Low permeability subsoil	1	20–30	40
	2.viii Peat	1	5–15	20
<i>Moderate</i> (M)	3.i Moderate permeability subsoil overlain by ‘well-drained’ soil	35	50–70	80
	3.ii Moderate permeability subsoil overlain by ‘poorly drained’ (gley) soil	10	15–30	50
	3.iii Low permeability subsoil	1	10–20	30
	3.iv Peat	1	3–5	10
<i>Low</i> (L)	4.i Low permeability subsoil	1	5–10	20
	4.ii Basin peat	1	3–5	10
<i>High to Low</i> (HL)	5.i High predicted permeability subsoils (sand or gravels)	30	80–90	100
	5.ii Moderate permeability subsoil overlain by well-drained soils	35	50–70	80
	5.iii Moderate permeability subsoils overlain by poorly drained soils	10	15–30	50
	5.iv Low permeability subsoil	1	5–10	20
	5.v Peat	1	5	20

Note that recharge to bedrock aquifer classes Pu and Pl is limited to $100\text{mm}\cdot\text{a}^{-1}$, and to Ll aquifers is limited to $200\text{mm}\cdot\text{a}^{-1}$. Areas of ‘made ground’ are assigned a recharge coefficient of 20%. Before full national groundwater vulnerability coverage was achieved in 2012, in unmapped regions the Extreme and High to Low vulnerability categories were used.

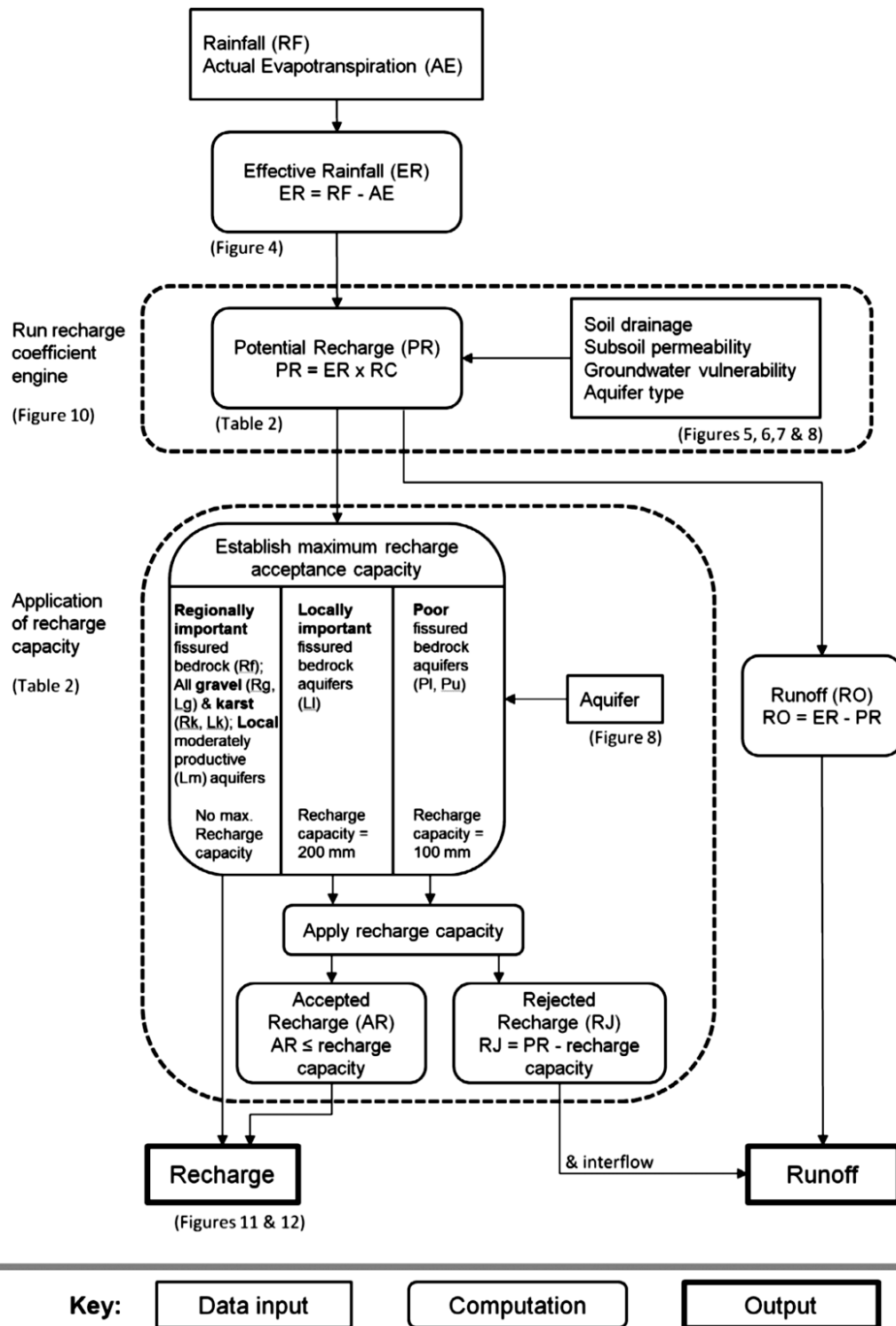


Figure 2.1: Indicative structure and method of the GIS-based tool for estimating recharge (Hunter Williams et al., 2013).

2.2 Hydrogeology of Irish Hard Rock Aquifers

As mentioned in Section 2.1.1, the bedrock of Ireland comprises Precambrian to Upper Palaeozoic igneous, metamorphic and sedimentary rocks. Limestones are the most common lithologies, underlying almost half of the country, and the Carboniferous limestones include the most important aquifers classified as 'regionally important' (Misstear et al. 2008). Nonetheless, most of the bedrock materials in Ireland are characterized by having a negligible primary but some secondary porosity developed as a consequence of the various deformation and tectonic episodes registered in the geological history of the island as well as weathering processes. These materials, as mentioned in the previous section, often constitute Poorly Productive aquifers. They typically present a system of fractures and fissures through which water flow occurs. Groundwater flow is, therefore, constrained by the properties of the fracture network (Comte et al. 2012).

Another determining factor in these type of aquifers is set by the reduction in fracture density and hydraulic activity with depth, which was first described by Davis and Turk (1964) and has also been described in Ireland by Fitzsimons et al. (2005), who considered the differences in fracturing with depth and the associated influence on transmissivity. The transmissivity of these aquifers depends on the fracture frequency but mainly on the interconnectivity between these fractures (Sánchez-Vila et al. 1996). In turn, this depends on the intensity of the structural stress, the lithology and the depth of burial (Hunter Williams, et al., 2019). Nevertheless, some authors argue that, in some cases, this permeability is not due to tectonic processes or unloading but to the effect of weathering processes (Lachassagne et al. 2011). This set of structural characteristics is translated into a low aquifer storage and throughput capacity, which govern groundwater dynamics in these aquifers within the Irish context. The consequences of these restricted capacities are twofold; first, the aquifers are not able to accept all the potential recharge resulting in a rejected recharge (Daly 1990) and second, groundwater flow occurs at a local scale when compared to the regionally important aquifers. In such cases, flow occurs over tens to hundreds of metres between recharge and discharge areas (Tedd et al. *(unpublished)*; Moe et al. 2010).

The inherent heterogeneity of fractured media is caused by the wide range of scales in which fractures occur; from microscopic to regional. For this reason, bedrock fractured aquifers are also described as fractal, which is often suitable for the characterisation of objects with scaling behaviour (Jiménez-Martínez et al. 2013). The main implication of this fractal geometry is the

impossibility of defining a representative elementary volume. Furthermore, this geometry also generates scaling effects of both transmissivity and storage coefficient. For instance, the increase of effective transmissivity with increasing scale. However, the scaling effect on transmissivity has been thoroughly investigated, whereas the scaling effect on porosity parameters and storage coefficient has received little attention in comparison (Jiménez-Martínez et al. 2013). Finally, the volume of water which can be stored in hard-rock aquifers is often not well determined because these aquifers are not usually important from the water-resource point of view (Comte et al. 2012). However, PPAs are still important in Ireland since there are a significant number of private water supplies depending on it (Misstear and Fitzsimons 2007).

Even though a large amount of literature exists about hard rock fractured aquifers at international level, there is limited existing research within Ireland. Daly and Hunter Williams in RPS (2008) proposed a conceptual model evidencing the differences with productive aquifers, and distinguishing four flow pathways: interflow, shallow groundwater, deep groundwater and discrete fault or conduit flow.

In 2006, the Environmental Protection Agency (EPA) installed a national groundwater monitoring network as a part of the implementation of the Water Framework Directive. This network consists of more than 220 monitoring points, most of which are located within PPAs. This monitoring network allowed projects such as the Pathways Project (Archbold et al. 2015) and the Poorly Productive Aquifers project (Comte et al. 2012; Cassidy et al. 2014; Cai and Ofterdinger 2016) to improve the knowledge on Irish fractured aquifers. In 2010, the EPA published a report presenting the monitoring results and the study of six selected catchments and proposed a conceptual model for PPAs. This conceptual model divides the aquifer into four pathways (Figure 2.2): (i) the **subsoils**, usually represented by glacial or alluvial sediments, (ii) the **transition zone (TZ)** – which was defined in the subsequent Pathways Project as “the weathered zone between the subsoil and bedrock” (Archbold et al. 2013), (iii) the **shallow bedrock** which is in the upper fractured zone, and it may or may not be weathered, and (iv) the **deeper bedrock** which corresponds to the deepest part of the section where the fractures are less frequent, especially in PPAs. The EPA report highlights that not all the catchments exhibit all four pathways. This is often the case for the TZ; which is not always present within PPAs, and it frequently presents a limited lateral continuity and with variability in thickness. Nevertheless, all research conducted up to date agrees on the crucial role that the TZ plays in this type of aquifer - when present - as it is considered the main natural pathway to transport flow and

solutes and it can constitute up to 50% of the flow within the aquifer (Fitzsimons et al. 2005; Daly, D. and Hunter Williams in RPS 2008; Comte et al. 2012; Deakin et al. 2015).

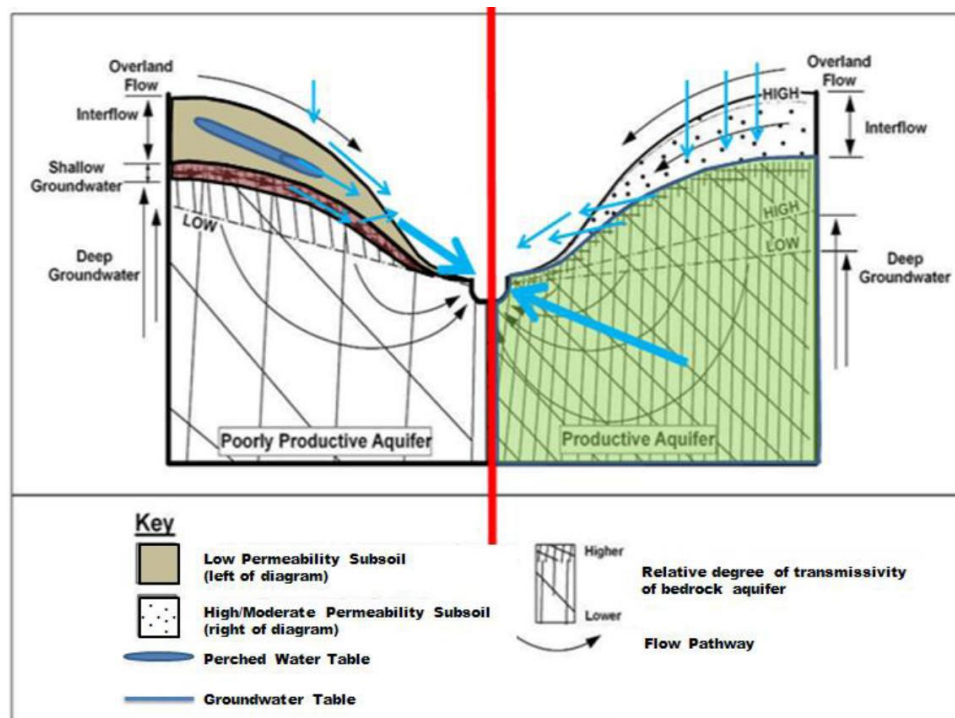


Figure 2.2: Conceptual model of PPAs (left) in comparison to a Productive aquifer (right). The principal pathways for each kind of aquifer are indicated on the sides. Extracted from Archbold et al. (2015).

As presented before, despite the prevalence of these types of aquifers in Ireland and their relevance in terms of water resources in rural areas, relatively little attention has been focused on quantifying the amount of water that PPAs can accept. The approach currently used is to apply a “cap” to the initially calculated recharge in order to set an upper threshold that annual recharge cannot exceed. In this way, the maximum recharge in areas underlain by poorly productive aquifers should be of 100 mm yr⁻¹ or 200 mm yr⁻¹ depending on the aquifer’s sub-category (Hunter Williams et al. 2013).

In the most recent years, a number of studies have tried to improve the characterisation of Irish hard-rock aquifers. Following the EPA report on PPAs, Comte et al. (2012), outline the main conceptual approaches to deal with fractured aquifers, identify the main challenges associated with its characterisation and set it into the Irish context (Figure 2.3). However, the core of the work is an integrated characterisation of three Irish catchments following a similar approach used by EPA, by combining geophysical methods (electrical resistivity tomography and seismic

refraction), borehole geophysical logging, structural mapping, hydraulic testing and water-table monitoring.

Generic lithological log		Terminology in tropical/arid regions (e.g. Africa, India) ⁽¹⁾	Terminology in temperate/cold regions (e.g. Eurasia, N. America) ⁽²⁾	Irish terminology ⁽³⁾	Refined terminology adopted for this study
REGOLITH	Overburden deposits	(generally absent)	Overburden/subsoil	Subsoil	Overburden
	Duricrust/paleosol	Laterite	(absent)	(absent)	(absent)
	SAPROLITE	Clayey saprolite	(generally absent)	(absent)	(absent)
	Sand-clay horizon				
	Decomposed bedrock	Sandy (laminated) saprolite	Upper weathered bedrock	Transition zone	Decomposed bedrock
	Broken bedrock	Saprock			Broken bedrock
SAPROCK	Fissured bedrock (interconnected and weathered fissures/fractures)	Fractured/fissured bedrock, Saprock	Middle fractured/fissured bedrock	Shallow bedrock	Fissured bedrock
	Unweathered bedrock (deep and poorly connected fractures)	Fresh/unweathered bedrock	Deep massive bedrock	Deep bedrock	Massive bedrock

(1) After Foster (1984), Acworth (1987), Wright and Burgess (1992), Chilton and Foster (1995), Dewandel *et al.* (2006), Lachassagne *et al.* (2011)

(2) After Krasny (1996), Durand *et al.* (2006), Krasny and Sharp (2007)

(3) After Moe *et al.* (2010)

Figure 2.3: Synthesis of the terminology commonly used to describe fractured aquifers. From Comte *et al* (2012).

As mentioned above, another characteristic of PPAs is their limited capacity to transmit water. Tedd *et al.* (*unpublished*) carried out a study to attain a better understanding of the throughput capacities of Irish poorly productive aquifers. For this purpose, three different calculation methods are used to estimate the throughput capacities: Darcy, throughput capacities (transmissivity estimated from Darcy equation) and Dupuit-Forchheimer calculations. Moreover, two different datasets are used: the national averages per aquifer type based on the GSI data (Kelly *et al.* 2015), and site-specific aquifer property data from the EPA. On one hand, the outputs obtained by using the GSI dataset (generic calculations) are higher than expected and are considered to be biased as (i) the GSI database is predominantly constituted by investigations related to water supply which have been successful and achieved higher than expected yields (Kelly *et al.* 2015), and (ii) the inherent limitations of yields assessments in private wells. On the other hand, the site-specific calculations lead to low capacities compared to the PPAs' maximum recharge capacities. As a conclusion, Tedd *et al.* (*unpublished*) propose that the correct capacities value probably lie between these two sets of outcomes.

In terms of groundwater recharge quantification, fractured aquifers present additional uncertainty due to their intrinsic heterogeneity and anisotropy, as discussed earlier. Similarly to Karstic systems, groundwater recharge can occur rapidly through preferential infiltration pathways. However, long term groundwater recharge depends on the entire fracture system, including low permeability fractures that can contribute to the long-term storage (Jiménez-Martínez et al. 2013). In Ireland, Cai and Ofterdinger (2016) carried out a recharge characterisation using a modified water-table fluctuation method (Crosbie et al. 2005) combined with time-series correlations analysis to quantify recharge in two Irish catchments: Gortinlieve (Co. Donegal) which is underlain by Precambrian micaschists and Glen Castle (Co. Mayo) which is underlain by a range of metamorphic Precambrian rocks. The results suggest recharge rates of 45-175 mm/y for the subsoil and 42-159 mm/y for the transition zone. The authors suggest that lower intensity rainfall events ($< 1\text{mm/h}$) have greater impact on groundwater recharge than higher intensity events ($> 1\text{mm/h}$). They also stress the usefulness of coupling the correlation analysis with the water-table fluctuation method.

Almost half of the Republic of Ireland is underlain by Carboniferous limestone, which constitutes the primary aquifer rock in Ireland (Drew 2008). Therefore, most Irish aquifers are fractured even though these discontinuities can be caused by different mechanisms and present contrasting hydraulic behaviour. These limestone aquifers are mainly on the lowlands, and their composition is pure enough to be susceptible to karstification processes (Drew 2008). Hence, in contrast with the hard-rock aquifers described previously, these fractured aquifers present enhanced porosity by dissolution processes which can create conduits and dominate the groundwater dynamics of entire catchments (Gill et al. 2013a), generate karst features such as sinkholes, and feed ephemeral lakes, which in Ireland are known as Turloughs (Naughton et al. 2012; Gill et al. 2013b).

2.3 Climate Change and Ireland's Climate

Climate has been naturally changing over the earth's history causing cold periods, such as glaciations, and warmer periods. During the last 150 years global temperatures have suffered a significant increase, with rises being more acute in the last half century (Figure 2.4). Historically, the climate changes experienced by the Earth were linked to tectonic processes, volcanic activity or changes in the incoming solar radiation. Nevertheless, the changes experienced in the last 150 years are partly due to some anthropogenic activities such as changes in land use, and the enhancement of greenhouse gas and aerosols emissions. To summarize, there are two drivers of the current changing climate: the natural forcing and the anthropogenic activities. The long-term change in climate patterns due to the conjunction of these two drivers is known as global change.

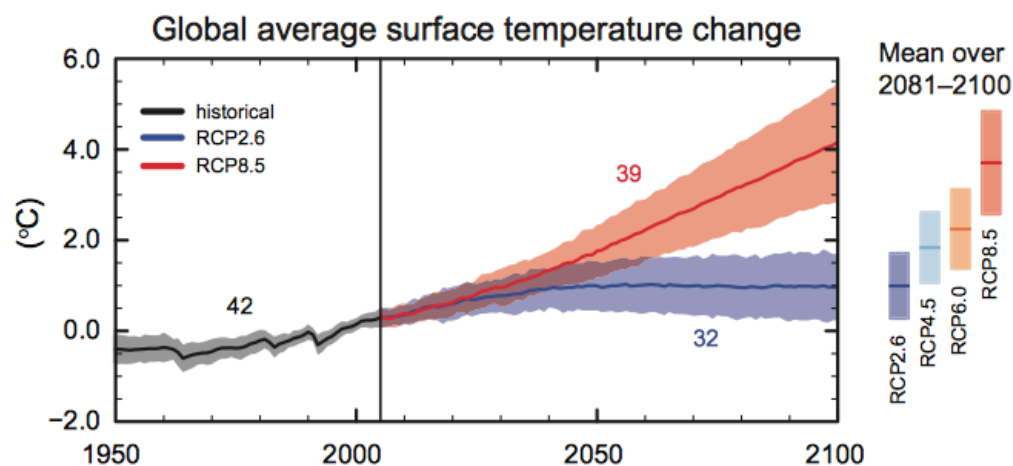


Figure 2.4: Temperature evolution in the last 60 years and projections until the end of the century under different representative concentration pathways. (Source: IPCC, 2014)

The *International Panel on Climate Change* (IPCC) is the leading body for the assessment of climate change. Since it was founded in 1988, its main aim has been to provide a scientific view of climate change knowledge and its possible environmental and socio-economic impacts. So far, IPCC has published five assessment reports, and a large number of special reports and technical papers. Consequently, an extensive literature exists about climate change modelling methods, trends and the effects of climate change at a global scale. However, studies at regional and local scale are also required so that the impacts can be estimated more accurately. Even though there are many studies at regional and local scale regarding surface water, groundwater has been much less studied (Taylor et al. 2013).

During the last decade a few research projects in Ireland have been focused on generating climate trends and projections for the country. McElwain and Sweeney (2007) found the changes experienced by the Irish weather, regarding temperature and precipitation, are consistent with those observed at global scale. Based on the prescribed set in the fourth IPCC report on Emission Scenarios (SERES), Sweeney et al. (2008) generated climate projections for the 21st century in Ireland. In this study several variables were downscaled using a statistical method for different Global Circulation Models (GCMs) and emission scenarios. Ensembles (or averages of the downscaled results) were then produced to evaluate the different model and emission uncertainties. The projections for temperature show a progressive warming during the last 100 years leading to an overall increase between 2.1 and 2.7°C by the 2080s. In addition, contrasts between seasons are likely to grow with the highest increases in temperatures predicted during the autumn period when the continental effect is more apparent. Regarding precipitation, the outcomes suggest a gradual rise in winter precipitation and a reduction in summer precipitation over the century.

Following the same line of research, a research project coordinated by Met Eireann generated updated simulations for Ireland, using the IPCC AR5 report (IPCC et al. 2013) as a baseline. The results obtained are similar to those found in the previous report: mean temperatures are likely to increase by approximately 1.5° by mid-century with respect to the reference period (1981-2000), and the warming is expected to be enhanced by the extremes. Concerning rainfall, winters are expected to be wetter and summers would become drier. Moreover, an increase in the frequency and intensity of rainfall events is predicted (Gleeson et al. 2013).

2.3.1 Modelling Climate Change

To date, the most common approach for investigating climate change and carrying out impact assessment studies has been the use of Global Circulation Models (GCMs), coupled with a range of downscaling techniques to obtain Regional Climate Models (RCMs) which are often then adjusted with Bias correction methods (Teutschbein and Seibert 2012). Even though this methodology has been the most common practice for the last three decades, it has a large inherent uncertainty and a number of shortcomings that must be considered when using these models. Hence, it is not surprising that in the last few years the number of critics has increased notably, not just amongst climate sceptics, but among the entire climate community. As a natural consequence of these differences between the scientific community, a few approaches have emerged to tackle climate change and impact assessment studies: the most common being

the use of GCMs either in a deterministic or probabilistic mode. For this reason, this section is mainly focussed on the presentation of the GCMs, RCMs and downscaling methods. However, literature around its limitations will be presented at Section 2.3.1.3.

2.3.1.1 Global Circulation Models and Regional Climate Models

The GCMs are numerical models representing the main physical processes occurring in the atmosphere and oceans and are based on fundamental equations such as the conservation of mass and energy, or the thermodynamic principles. For these models, the spatial and temporal evolution of climate are obtained as a function of the initial and boundary conditions set. The boundary conditions were typically set by climate scenarios which are defined by the IPCC as a plausible description of a future world. These scenarios included variables such as technological development, demographic growth, and greenhouse gas emissions. In this way, several “alternative images” of a future world could be used to force the GCMs. However, in the last report released by the IPCC (2013), the scenarios have been substituted by Representative Concentration Pathways (RCPs). Instead of using socioeconomic “storylines”, each RCP describes an emission and concentration pathway by 2100. From this baseline, researchers can test various permutations of socio-economic circumstances called “narratives” which are equivalent to the previous “storylines”. Even though regional information can be obtained from GCMs, their horizontal resolution is too coarse to be applied directly to regional studies. Therefore, a regionalization of the models is required. This is done by applying downscaling techniques which – simplifying - can be divided into statistical or dynamical approaches. Finally, although GCMs simulate the physical processes, the results of these models are highly uncertain due to inadequate representation of the climate system, unknown greenhouse gas emission scenarios and initial conditions (Woldemeskel et al. 2014). Other significant sources of uncertainty are the climate natural amplifiers as they can generate feedbacks, which are extremely difficult to define, characterize, and quantify. A clear example of this phenomenon are clouds; it is still uncertain the role that they can play in a future climate since high level clouds increase temperature, but low clouds tend to decrease it (Randall 2007).

2.3.1.2 Downscaling methods

Regarding climate modelling, although other approaches have been suggested, projections from global and regional climate models (GCMs, RCMs) are the default tool for generating future climate projections as an input into recharge and hydrogeological models in impact studies. General circulation models (GCMs) are the primary tool to provide global simulations for future

climates. However, as discussed, their coarse resolution makes them ineffective in terms of reproducing climate scenarios at regional or local scales, since local features such as topography, water bodies or local climate variability occur at a finer scale than that reproduced by the GCMs. This causes the inability of GCMs to reproduce climate heterogeneity at a local or regional scale and leads to the need for a scale reduction. In response to this need, various downscaling methods have been developed to address the resolution gap. The choice of downscaling method depends on various factors such as the desired scale. However, this choice has a number of implications which must be taken into account.

The two most common downscaling methods are the dynamical and statistical methods. Dynamical downscaling methods are based on the application of regional circulation models using the GCMs as boundary conditions. In other words, dynamical methods are based on including data and physical processes in models similar to GCMs but covering a limited area. These types of datasets have a large number of advantages, the most important one being their ability to respond in physically consistent ways to different external forcing such as variations in greenhouse gas concentration, or solar radiation (Wilby et al. 2000). Moreover, RCMs often reach a higher resolution than the outputs obtained by statistical downscaling, so the use of RCMs is recommended when a finer resolution is required. However, this technique is computationally intensive, and its quality obviously depends on the quality of the GCM used to define the boundary conditions. Furthermore, RCM outputs are still subject to systematic errors and therefore often require a bias correction as well as further downscaling to achieve a higher resolution (Schnarr and Trzaska 2014).

Statistical downscaling methods, in contrast, are based on establishing statistical relationships between large-scale climate features (predictors) and local climate characteristics (predictands). This approach assumes that the relationships remain valid under climate change conditions and that the predictor set captures the signal of future climate (Wilby et al. 2000). Despite the resolution of the outputs being coarser than that obtained by dynamical downscaling, the statistical approach is appropriate for areas of 20 km² and larger, and has the clear advantage of a lower computational demand. Schnarr and Trzaska (2014) reviewed the downscaling methods for climate change projections, and summarized the main characteristics, advantages and disadvantages of these two methods as set out in Table 2.3.

In the IPCC fifth assessment (2013), there is a specific chapter dedicated to evaluating the performance of climate models, including downscaling techniques. A synthesis of the improvements of the downscaling methods since the previous assessment is also presented. However, it is stressed that the quality of the downscaling varies with location, season, parameter and boundary conditions. In other words, there is no single downscaling technique which is always better than another, but a best method depends on the purpose of the modelling, and the other variables mentioned earlier. Another highlighted fact is that model performance does not increase linearly; for example, the performance of the projection can improve more when passing from 50 km to 25 km than when passing from 25 km to 16 km. However, with other techniques and variables the improvement is larger at smaller scales. It is also stressed that there is no single model with higher performance in all variables, but there are a few models that are able to represent certain phenomena more accurately. To summarize, there is no combination of downscaling method and model that performs better for all the variables and for all the locations, but the modelling skills depend on a significant number of variables. Therefore, the choice of climate modelling will depend on the quality of the data over a certain area and scope of the study and is therefore partly subjective since it will rely on the researcher's criteria.

Table 2.3: Synthesis of the main characteristics of the statistical and dynamical downscaling methods. Modified from Schnarr (2014)

	Dynamical downscaling	Statistical downscaling
Requirements	-High computational resources -High volume of data inputs -Reliable GCM simulations	- Medium/low computational resources -Medium/low volume of data inputs -Good quality observational data -Reliable GCM simulations
Advantages	-Based on consistent, physical mechanisms -Resolves atmospheric and surface processes at sub-GCM grid scale -Not constrained by historical record -Available for uncertainty analysis	-Computationally inexpensive and efficient -Flexible methods possible to tailor for specific purposes -The same method can be use in different regions -Relies on the observed climate -Can provide point-scale climatic variables for GCM-scale output
Disadvantages	-Computationally intensive -Typically driven by only one or two GMC/emission scenario simulations -Requires further downscaling and bias correction -Results depend on RCM assumptions; different RCMs will give different results -Affected by bias of driving GCM	-High quality observed data required -Stationarity assumptions -The simplest methods provide projections at a monthly resolution
Applications	-Country or regional level assessments with significant government support and resources -Planning by government agencies across multiple sectors -Impact studies that include various geographic areas	-Crop-yield, water, and other natural resource modelling and management -Delta or change factor method can be applied for most adaptation activities

In addition, it has been demonstrated that different downscaling methods can lead to variable results, and the range of variation can be as large as the range between different models (Seguí et al. 2010). Similarly, when bias corrections are required, the outcomes present the same range of variation when applying different bias corrections to a given RCM (IPCC et al. 2013).

2.3.1.3 Limitations and discussion

The use of GCMs and RCMs is the most widespread approach to simulate climate change at different scales; this became apparent in the last IPCC report, where almost all the impact study assessments on water resources presented followed this approach. As presented in Section 2.3.1.1, GCMs are mathematical models that have been developed to associate specific GHG emissions with plausible future climate scenarios (Kundzewicz and Stakhiv 2010). As a result, plausible climate projections are obtained. However, these models reproduce basic physical mechanisms and feedbacks. For this reason, even though they can generally represent some climate variables at continental scale, it is necessary to apply downscaling methods (statistical or dynamical) in order to simulate regional-scale phenomena. Nevertheless, we must keep in mind that an increase in temporal or spatial resolution does not necessarily imply that the confidence that we have in the projection is increased (Wilby et al. 2000). For example, often the downscaled output models are still unable to simulate local conditions caused, for example, by topography.

In recent years, the shortcomings of this approach have become increasingly apparent; for instance, these models are unable to reproduce the past climate as demonstrated in Anagnostopoulos et al. (2010), or they show different reactions to specific local behaviours such as storminess (Shepherd 2016). Whereas some authors have tried to address this large uncertainty by quantifying it (see Section 2.4.2), it is a more common practice to use a large number of RCMs and then use the mean ensemble as a significant projection to draw conclusions. Even though it is a widely accepted practice, and a large part of the community accepts it as a first approach to characterize uncertainty (e.g. Knutti et al. 2013) some authors contend that the spread in the ensemble projections is not an uncertainty quantification because it does not represent a meaningful probability distribution (Shepherd 2016). In addition, Knutti et al. (2013) found evidence that suggests that different GCMs, and consequently RCMs, are interdependent. The authors state that, as a consequence, the different models share flaws, which increases the difficulty of interpreting such ensemble models. The danger, however, is that this goes largely unnoticed. All these shortcomings are discussed in

papers such as Kundzewicz (2010), which synthesises the main issues, or Wilby (2010) which also presents an alternative. (Wilby 2010), distinguishes between a “top-down” or “scenario-led” approach, which is what we have presented so far, and a “bottom-up” approach, which is focused on reducing the system vulnerability to past and present climate. However, it is highlighted that this approach is constrained by the availability of long-term datasets. Other authors present similar approaches with different names: Hazeleger et al. (2015) calls them “Tales” whereas Shepherd et al. (2018) call them “Storylines”; however, the concept behind this different nomenclature is fundamentally the same: the use of past events to analyse the vulnerability of different systems.

2.4 Climate change and groundwater resources

Little doubt remains about the ongoing climate change since there is clear evidence for it. Nevertheless, it is still not clear how it will affect freshwater resources. Global warming is related to some of the hydrological cycle components such as changes in temporal distribution of rainfall, its intensity and the extreme values, so it is acknowledged that the hydrological cycle will be intensified as a consequence of climate change. For this reason, it is also commonly accepted that water resources are vulnerable to climate change. Some authors have recently provided evidence of the influence of a changing climate on the hydrological cycle (Döll 2009).

As Alley (2016) points out, groundwater resources are defined by a large storage capacity in relation to the incoming flows and, for this reason, it is generally assumed that they will be available in times of drought. Nonetheless, instead of mitigating the drought effects, inaccurate management of groundwater resources can lead to an overexploitation of these resources and so to an intensification of the impacts of the drought.

In addition, it should be considered that, in the context of climate change, irrigation schemes and water demand can be modified significantly, thereby increasing the pressure on groundwater resources. In this way, climate variability will have an impact on groundwater resources directly by constraining the recharge rates and indirectly through changes in groundwater use (Taylor et al. 2013). The induced pressures due to anthropogenic activities are also stressed in the strategic overview paper on global change and groundwater published by the International Association of Hydrogeologists (IAH, 2016). In this publication it is stated that changes in land use such as deforestation or intensification of agricultural activities can lead to

changes in recharge rates or induce diffuse pollution. In some areas these changes have already had important impacts on groundwater.

2.4.1 PE estimations and climate change signal

It is accepted that the projections of some variables are more robust than others. The reliability of a variable's projection depends on the complexity of its prediction and whether or not it is calculated from other projected variables. For example, temperature projections can be estimated more accurately than rainfall as the latter is a conditional process and so both its occurrence and intensity need to be predicted. In the case of potential evapotranspiration (PE), its projections are an important source of uncertainty in water resources impact studies for two primary reasons: firstly, PE estimations under current climate present a significant intrinsic uncertainty, and secondly, future PE estimations are calculated from the projection of other predicted variables so there is an accumulation of uncertainty and error.

It is necessary to have reliable PE estimations to be able to calculate groundwater recharge accurately. However, as mentioned above, it is well known that PE estimations are usually a source of uncertainty given the difficulty of having direct estimations and the necessity to approximate some of the variables needed to compute it. For this reason, there is a large amount of literature describing the ET processes but also a large number of methods to estimate it: more than fifty according to Lu et al. (2005). The choice of one method or another is subject to data availability and, again, the criteria of the researcher. Nevertheless, in an attempt to standardise the calculation process, the Food and Agriculture Organization of the United Nations (FAO) recommended the use of the modified Penman-Monteith since it is considered the best calculation method when there is enough data available (i.e. air temp, wind speed, pressure, net radiation, etc) (Allen et al. 1998b). The FAO presents guidelines to compute some of the variables required by the Penman-Monteith method; however, the use of the Hargreaves equation is recommended in the case of limited data availability (i.e. temperature only). In addition, there is a growing awareness of the need to understand PE response under climate change.

Similar to the existing discrepancy about which PE method to use under the current climate, there is also disagreement about climate projections. Some authors suggest that the use of different PE methods can lead to different climate change signals (Kay and Davies 2008). In this way, in the field of impact assessment studies, there seems to be no common approach to the

estimation of PE and its inherent uncertainty; some studies use the Penman-Monteith method, using projections of all the variables including wind speed and air moisture, while others prefer to use simpler methods with more reliable downscaled variables such as Hargreaves (Hargreaves and Samani 1985), Priestley-Taylor (Priestley and Taylor 1972), or Blaney - Criddle (Blaney and Criddle 1950).

In addition, Kingston et al. (2009) also identified a gap in the understanding of the consequences of using different PE methods for global water balance calculations. In order to bridge this gap, six commonly used PE methods were applied at global scale for a scenario with 2°C rise in global mean temperature with respect to a baseline period (1961-1990). Nevertheless, the characterization of the PE signal in climate change is identified as an important contributor to the overall uncertainty of the future water balance and freshwater estimations.

2.4.2 Climate change and groundwater recharge

Because an intensification of the hydrological cycle is predicted, the impacts of climate change on surface water have been studied due to its visibility and the clear flooding and drought risks involved. Despite the vital importance of groundwater resources, the impacts of climate change on groundwater resources have received much less attention.

In fact, the IPCC fourth report (2007) stated that there had been little research regarding the impacts of climate change on groundwater and that the few existing studies only provided results for very specific areas and conditions. In response to this knowledge gap, there has been an increasing focus on climate change in relation to groundwater in more recent years (Green et al. 2011; Crosbie et al. 2013; Taylor et al. 2013). Holman et al. (2012) stated that, as evidence of the lack of research on this topic, no standardized methodology existed to carry out this type of research, referring to the large number of approaches that are available to evaluate climate change impacts on groundwater. In the same work, a number of recommendations for hydrogeologists to address groundwater-related climate change impact studies were compiled. Subsequently, some researchers have taken some of these recommendations into account in their research projects (Dams et al. 2012; Sulzbacher et al. 2012; Kidmose et al. 2013; Kurylyk and MacQuarrie 2013; Raposo et al. 2013). Green et al. (2011) wrote the first exhaustive review paper in which the relationships between climate change and groundwater recharge were explored. In another vein, Taylor et al. (2013) wrote a review of the possible impacts (direct and indirect), feedbacks and gaps for this research topic.

The publication of the IPCC fourth report caused a reaction within the groundwater community, which started to assess the impacts of climate change. Thus, in the fifth IPCC report (2013) it was noted that the number of studies regarding the impacts of climate change on groundwater has increased significantly since the previous report, even if most of the studies have still focussed at a local scale. Just a few projects had tried to assess the impacts at large scale, including continental scale in Australia (Döll 2009; Crosbie et al. 2013). More recently, Moeck et al. (2016) studied the uncertainty propagation through different types of hydrological models when estimating groundwater recharge as previous research suggested that the choice of the recharge estimation technique has a large control on the outcoming signal (Crosbie et al. 2011). In this work the need to capture climate extremes (model transferability) is emphasised and it is recommended to use several hydrological models.

Similar to the situation globally, in Ireland there have been a number of research projects centred on generating climate projections and their impacts on surface water (e.g. Steele-Dunne et al. 2008; Sweeney et al. 2008; Bastola et al. 2012; Gleeson et al. 2013), but just two studies have tried to look at the impacts on groundwater (i.e. Murphy and Charlton 2006; Sweeney et al. 2008). In both papers changes in catchment storage are studied by applying the rainfall-runoff (CRR) model HYSIM in nine Irish catchments. This CRR model uses daily rainfall and potential evapotranspiration data to simulate river flow and it is combined with the generalized likelihood uncertainty estimation (GLUE) method to quantify the uncertainty associated with the overall modelling process. The results are analysed catchment by catchment and, as a general conclusion, it is shown that changes in rainfall and temperature are likely to lead to significant changes in groundwater hydrology. In turn, the aim of Williams and Lee (2010) was not to quantify the impacts but to assess them qualitatively; Irish aquifer characteristics, national water usage, groundwater recharge and groundwater environmental needs are evaluated with respect to the possible impacts of climate change, including changes in rainfall patterns and groundwater recharge (among others). In summary, to date, there is a limited number of studies assessing the possible impacts of climate change on Irish groundwater resources. Furthermore, the studies described above are fairly general assessments and hence more detailed quantitative research on this topic is needed. More recently, Morrissey et al., (2020), investigated the possible impacts of climate change on groundwater flooding and ecohydrology of the Irish lowlands.

Uncertainty assessment of impact studies

As has been explained previously, there is an intrinsic uncertainty associated with the use of GCSMs with the corresponding downscaling techniques. In the case of impact studies regarding groundwater recharge we also need to consider the uncertainty of PE groundwater recharge calculations, and other sources of uncertainty such as aquifer and subsoil properties. Wilby (2005) synthesized the situation stating that “when modelling the impact of climate change on water resources there is a cascade of uncertainty that begins when future socio-economic story lines are translated into future emission scenarios and ends with the impact modelling”.

As discussed in Section 2.1, the uncertainty of groundwater recharge calculations is usually assessed by applying more than one method. Similarly, the impact studies on groundwater have typically “quantified” the overall uncertainty by using different GCMs and emission scenarios. However, the disparity in results obtained when applying two different GCMs or emission scenarios, is significantly larger than when applying two recharge calculation methods and, as a consequence, in some cases it has not been possible to determine the signal of the change in recharge (positive or negative) (Hagemann et al. 2011) .

Another common approach – though less frequently used than the approach mentioned before - is to run the calculations with a large combination of GCMs and scenarios, and then ensemble the results and force the hydrological or hydrogeological model using the ensembles as an input (see Section 2.3.1.3). As a result of applying this approach a range of likely values can be established with a best estimation corresponding to the mean ensemble. Finally, the less common approach consists of quantifying the uncertainty associated with the overall calculations by using an objective metric; for example, Woldemeskel et al. (2014) proposed a framework to quantify uncertainties specifically to be used for impact assessment studies. This framework consists of three steps: (1) applying a nested bias correction to the GCMs, (2) quantifying the possible uncertainties using square root variance as an indicator and (3) accounting for the uncertainty of parameter estimation on the impact models by using simulation-extrapolation. Nevertheless, it must be remembered that it has been demonstrated that the choice of the bias correction method has an impact on the results as large as the choice of the selected climate model (IPCC et al. 2013). Furthermore, Hagemann et al. (2011), studied the impact of bias correction on impact studies and they found that the bias corrected data changed the signal of the change for specific locations and months.

3. General Research Approach and Study Areas

In this chapter the general methodology and materials employed to address the research questions proposed in Chapter 1 are presented. This chapter is subdivided into two main sections: the first in which an overview of the general methodology is presented, and the second introducing the selected study areas, and the data available for each one of them.

3.1 General Research Approach

In this section an outline of the research strategy followed during this thesis is presented. However, detailed explanations of the methods used will be provided within the corresponding results chapters for better clarity and to reduce repetition. The research approach followed during this project has been mostly based on the outcomes of the literature review (see Chapter 2) in an attempt to bridge some of the main knowledge gaps identified in the bibliography regarding the impacts of climate change on groundwater resources in bedrock aquifers in Ireland.

As presented in Chapter 2, climate change is expected to affect the groundwater resources by causing an intensification of the hydrological cycle. However, it is also known that local geological features affect the magnitude of these impacts. In order to have a first assessment of which variables have a larger control on groundwater recharge within the Irish context, a sensitivity analysis was carried out considering both hydrometeorological and hydrogeological variables (Chapter 4). This initial sensitivity assessment was performed using the recharge coefficient approach since it is a simple method that has proven useful in providing initial recharge estimations within Ireland and takes into consideration all the variables of interest (Misstear et al. 2009a; Hunter Williams et al. 2013).

The characteristic hydrogeological features of Ireland are known to have an important control on the amount of water reaching the water table (Section 2.1). In fact, these characteristics have typically underpinned the recharge methods used within the Republic of Ireland. It is for this reason that in this thesis both the subsoil's infiltration capacity and the aquifer's storage capacity have been investigated for selected study areas. Firstly, the intrinsic error associated with the PE estimation techniques is assessed by comparing the results obtained by applying several methods, with Met Éireann data. Secondly, these data are used to calculate the soil

moisture budget following the FAO recommendations (Sections 5.2.1 and 5.2.2). Then, the infiltration capacities of two additional study sites are evaluated by modelling the infiltration processes through the unsaturated zone using the model Hydrus 1D (Simunek et al. 2012). This software package was selected because it is able to simulate water flow in partially saturated soils, while allowing the discretization of the soil profile and specification of a range of boundary conditions. The availability of high-resolution soil moisture content data allowed a good adjustment of the hydraulic parameters of the soils, to increase progressively the amount of rainfall until runoff was generated (section 5.3.3).

Because of the impossibility of measuring the storage capacity of the aquifers directly, a recharge characterisation exercise was carried out for two different study catchments. A number of recharge calculation methods were applied to each of the catchments to constrain recharge uncertainty and use it as a proxy to assess the specific yield (Chapter 6). A range of methods were selected based on data availability while keeping in mind that each estimation technique calculates a slightly different type of recharge, which then provides useful insights about the recharge processes and the conceptual models of the catchments. The approaches applied include: the water table fluctuation method (Crosbie et al. 2005), baseflow separation, Dupuit-Forchheimer calculations and the NAM rainfall-runoff model (Nielsen and Hansen 1973) among others.

According to the fifth IPCC report (2013), it is likely that human influence has contributed to the observed changes in global temperature as well as the changes in intensity and frequency of extreme events such as droughts and flooding. However, it is still complicated to identify to what extent these events are due to anthropogenic modifications or to natural forcing and internal variability. For example, the Irish climate (and its extreme events) is strongly influenced by large-scale circulation patterns such as the winter North Atlantic Oscillation (NAO) (Comas-Bru and McDermott 2014). In other words, it is necessary to understand the natural variability of the climate and how it affects the groundwater resources before being able to attribute any variation to climate change. In Chapter 7, Continuous Wavelet Transforms (CWT) and Wavelet Coherence (WTC) are used to: (i) evaluate the cyclicity of rainfall and temperature series, (ii) compare the signals of the patterns mentioned above with rainfall and temperature series, (iii) assess how this variability affects groundwater resources, and (iv) how it can be used for better water resources management.

Once the link between hydroclimatic variables and groundwater levels is established, the possible impacts of climate change can be evaluated in the study areas (Chapter 9). Impact assessment studies have traditionally consisted of forcing hydrological models with climate projections. In this case, the NAM rainfall-runoff model implemented for the recharge characterisation has also been used to generate long-term recharge scenarios by forcing it with a total of 10 future climate permutations (5RCMs and 2 RCPs). The NAM model was considered appropriate for this purpose as it has been previously successfully implemented in Irish catchments to simulate groundwater pathways (e.g: O'Brien et al. 2013; Archbold et al. 2015), and also because it has been used in international climate change impact assessment studies (Thodsen 2007). However, it was considered crucial to represent the strong control exerted by the local hydrogeological settings (such as the limited storage capacity) when generating future recharge scenarios. For this reason, a methodology coupling Wavelet Transforms (WT) and Artificial Neural Networks (ANN) was developed and implemented for the study catchments (Chapter 8). This method uses Discrete Wavelet Transforms (DWT) to decompose the input time-series (rainfall, temperature and PE) and Nonlinear Autoregressive Networks with Exogenous Inputs (NARX) to forecast monthly groundwater levels for up to one year. Because of its data-driven structure, it is considered that the hydrogeological settings are taken into account implicitly in the model. The WT-NARX is also used in Chapter 9 to assess the impacts of climate variability by first forcing the WT-NARX model with climate projections, and then with modified time-series with the SDSM-DC software as was done previously for the catchment scale sensitivity analysis (Section 4.2.1.2).

3.2 Groundwater Recharge Study Catchments

3.2.1 Introduction

In this section, the two main study catchments -plus an additional catchment- studied during this thesis are presented. In order to be able to transfer knowledge from these catchments to other areas in Ireland, the individual study catchments were chosen to reflect a range of typically Irish hydrogeological settings. However, given the theoretical desk-based nature of this project (i.e. there was no field work involved), the selection of the study areas was subject to data availability as well as the existence of previous studies. Because this project is mainly focused on Poorly Productive Aquifers, two catchments fully underlain by PPAs were selected: the Mattock and the Dripsey. Despite this common feature, the two catchments present contrasting

characteristics in terms of lithology, aquifer category and climate. Additionally, a third catchment, the Nuenna, was selected because of the contrasting characteristics within the catchment: even though most of the catchment is represented by a regionally important aquifer, the borders, are underlain by PPAs. In other words, the catchment is partially affected by recharge caps, which exemplifies the contrasting behaviour between important aquifers and poorly productive aquifers. The Nuenna catchment was solely investigated during the early stages of this project, to compare the hydrogeological behaviour of the two aquifer categories (Chapter 4) and the PE methods uncertainty (Chapter 5). The Mattock and the Dripsey have then been investigated as study cases throughout the thesis.

These catchments were selected from a short list of potential catchments using a range of criteria to rank them. These criteria included, for example, land use, catchment size, subsoil type, etc. However, as mentioned above, in this project the data availability was crucial in the selection process. Both catchments were part of the PPAs project conducted by EPA and consequently had groundwater monitoring points at different depths and locations (CDM and OCM 2010a, b). The Mattock (and the Nuenna) catchment had been thoroughly investigated as a part of the Pathways Project (e.g: Archbold et al. 2015). In contrast, the Dripsey has been studied mainly for nutrient transport and flooding risk purposes (Jordan et al. 2005; Kiely et al. 2008; Doody et al. 2012; Ali and Bruen 2016).

Figure 3.1 shows the geographical localization of the three study catchments within Ireland as well as the situation of the Knocktopher borehole, which is used in Chapter 7 as complementary groundwater data to contextualize the results obtained for the Mattock and the Dripsey (see Section 3.2.5).

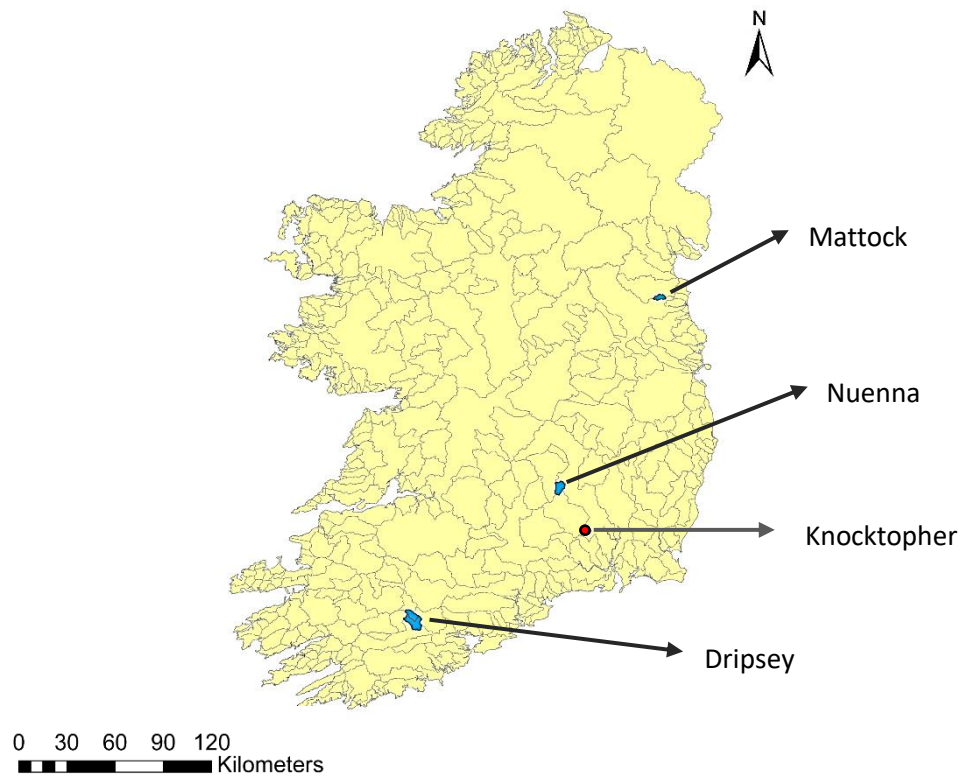


Figure 3.1: Situation of the three selected study catchments (blue area) and the additional groundwater levels (red circle).

3.2.2 Mattock Catchment

The Mattock catchment has an approximate area of 17 km² which is divided between Co. Meath and Co. Louth. The Mattock River is a tributary of the Boyne; it has an estimated length of about 7km from the headwaters to the discharge measuring point, which is called Berril's Farm. The actual outlet of the catchment is located several kilometres downstream at its confluence with the river Boyne. Figure 3.2 shows a clear topographic gradient from the headwaters, with a maximum of 242 mOD, to the gauging point which is at 80 mOD. This figure also shows the location of the groundwater level monitoring points.

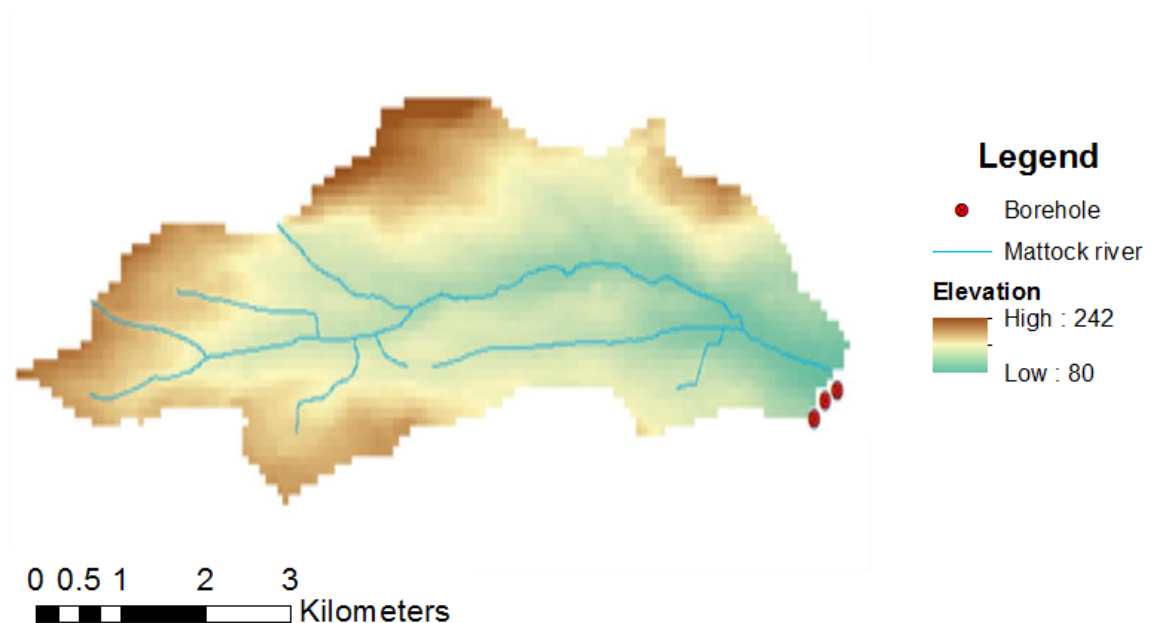


Figure 3.2: Digital elevation model of the Mattock catchment showing the topography of the study area. The river is represented in blue and the groundwater monitoring points are presented by red dots.

3.2.2.1 Catchment characteristics

A GIS analysis, using the land-use and cover data from EPA, revealed that the principal land uses over the catchment are pasture (88%) and tillage (8%), with forests representing about 2%, similar to the urban areas, which are mainly concentrated around the town of Collon (approximately 2km from the gauging point). The catchment is mainly covered by poorly drained soils with patches of well drained soils in the borders of the watershed and in small areas in the centre. These poorly drained soils overly glacial tills which are usually around 4 m thick. However, geophysical surveys showed that in the lower parts of the catchment the thickness of these deposits can be nearly 30 m (CDM and OCM 2010a). In addition, complementary geophysical surveys revealed the presence of a paleochannel between boreholes MK2 and MK3.

The underlying bedrock can be divided into three main classes: 1) the top of the catchment is underlain by black Silurian mudstones, siltstones and greywackes that correspond to the Rathkenny Formation; 2) the centre of the study area is composed of an amalgam of Ordovician volcanic and metasediments belonging to 9 different geological formations; and 3) the area surrounding the gauging point is formed by Silurian calcareous greywackes. It must be highlighted that the whole extent of the catchment is affected by fractures from local to regional scale with a NE-SW orientation (Figure 3.3).



Figure 3.3: Bedrock map of the Mattock catchment. The different formations constituting the bedrock of the catchment are presented in different colours according to the legend at right. The faults are represented by black lines (Data source: GSI)

3.2.2.2 Hydrology and Hydrogeology

The average annual rainfall over the Mattock is 913 mm and the mean potential evapotranspiration is 501 mm, according to data obtained from Dunsany synoptic station (Met Eireann) for the study period (2012-2015) for which there was available data for all the water balance components. The average estimated actual evapotranspiration for the same period is 463 mm which represents 92% of the PE and so, the effective rainfall is about 450 mm per year. The mean annual discharge observed at Berril's Farm during the same period is equivalent to 479 mm according to the gauging carried out by the EPA.

The Mattock catchment presents the full range of groundwater vulnerability categories that vary depending on the subsoil type and its thickness. Vulnerability ranges from moderate to extreme in the areas with patches of sands and gravels, and from low to extreme in the areas

covered by tills. These spectra of categories are due to the natural changes of thickness of the subsoils, with higher vulnerability when the bedrock is closer to the surface.

The Silurian rocks of the Rathkenny formation, and the Ordovician metasediments constitute poor aquifers, which are generally unproductive except for local zones (PI), whereas the Silurian calcareous greywackes in the east side of the catchment are Poor aquifers which are generally unproductive (Pu), according to the GSI classification. Both categories have a corresponding recharge cap of 100 mm/y.

3.2.2.3 Conceptual model

As presented above, the Mattock is a rather small catchment, with significant slopes and covered with low permeability subsoils. The combination of these features generates a fast response from the river to rainfall events, giving the Mattock a “flashy” runoff behaviour. The groundwater discharge point is downstream of the delineated boundaries, furthermore, the bedrock water levels are lower than the river in the vicinity of Berril’s Farm, which indicates that the hydrologic and hydrogeologic catchments are not matching in this case. The geophysical characterisation carried out by EPA/GSI suggests the presence of a paleochannel with perched water tables in the interbedded alluvium. In addition, close to the monitoring point MK3, there are two areas of intense faulting. Finally, the EPA report highlights the exceptionally high specific yields observed at the MK3 cluster of boreholes and concludes that it may be due to extractions nearby (pumping wells), or a discharge point downstream even though there are no springs known in the vicinity. The presence of any type of discharge point near to the MK3 cluster of boreholes -where there are upward gradients - would generate higher gradients that could be translated in high apparent specific yields.

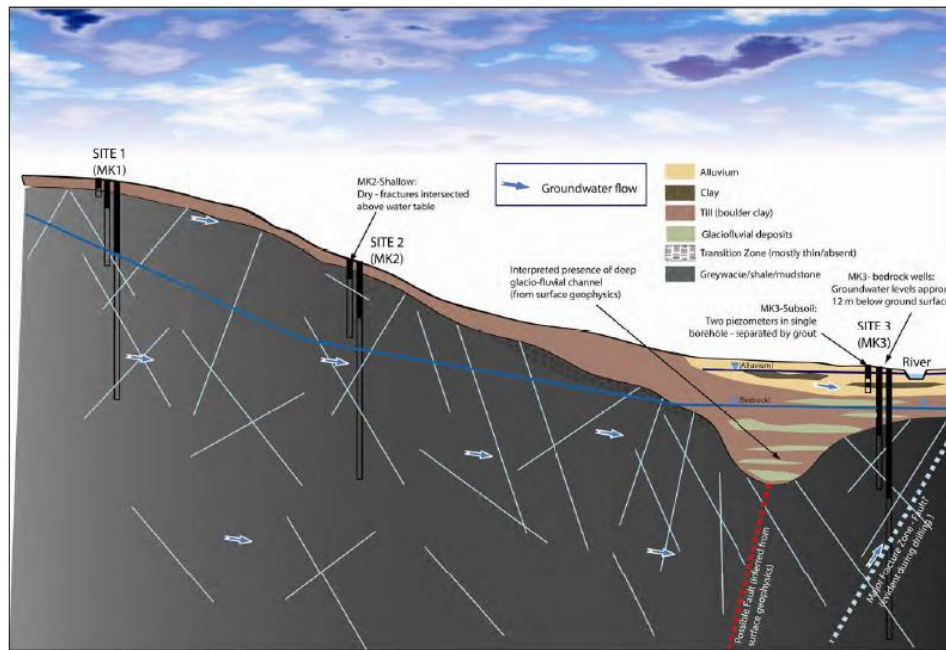


Figure 3.4: Synthetic conceptual model of the Mattock catchment. The cross section presents the location of the three monitoring points and the depths of the measurement wells. It also shows the main hydrogeological features of the catchment, inferred from observations on the study area. Source: CDM and OCM (2010)

Figure 3.4 presents a schematic cross section summarising the conceptual hydrogeological model for the Mattock catchment. As can be observed, the groundwater flows from upslope (MK1) towards the river (MK3). Furthermore, this catchment presents two features that differentiate it from many other fractured bedrock aquifers: firstly, the absence of transition zone between the subsoils and the bedrock and, secondly, the hydraulic disconnection between the river and the water table (Archbold et al. 2015)

3.2.2.4 Available Data

Because the Mattock catchment was included in both the Pathways project and the EPA project on PPAs, it is well instrumented. As shown above in Figure 3.3, there are three clusters of boreholes monitoring groundwater levels at 15 min resolution from 2008, when they were installed, up to the present time. However, the data of the MK2-shallow and MK3-deep monitoring points were not used in this study due to long data gaps. For the rest of the time-series, missing data were filled in with linear interpolation. Additionally, the noise generated by the transducer was removed by applying high band Fourier transforms. Where this technique could not fully de-noise the dataset, the affected points were deleted and interpolated as missing data.

In this catchment there are three hydrometric stations: the Collon Weir, Diversion Weir and Berril's Farm. These stations correspond to points in which the study area can be further subdivided. However, given the nature of this project, only the discharge data of Berril's Farm has been used. This dataset, which was provided by the EPA, starts in 2011 and continues up to date, and has a 15 min resolution.

Different meteorological datasets have been used for this catchment during the thesis depending on the purpose (Table 3.1). During the sensitivity analysis and soil moisture budgeting (Chapters 4 and 5), where long-term rainfall and PE were required (1985-2015), rainfall data were obtained from the Mellifont rainfall station which is located approximately 4 km away, and PE from Dublin airport Synoptic Station which is 40km away approximately. For the rest of the project, rainfall and PE data from the Dunsany rainfall station (which is 7 km away) was used as long-term datasets were not necessary but hourly resolution was required. These datasets were used in Chapter 6 for the period 2010-2015, and from chapter 7 onwards, for the period 2010-2018. However, the implementation of the NAM rainfall-runoff model over the Mattock required high resolution rainfall data, given the small size of the catchment. Hence, additional rainfall data from a previous PhD project was used (O'Brien 2013). This dataset contains precipitation measurements from a rainfall station within the catchment at hourly resolution for the 2011-2012 period.

Table 3.1: Summary of the available datasets for the Mattock catchment and their application throughout the manuscript. T stands for Temperature, PE for Potential Evapotranspiration, SMB for Soil Moisture Budget and GWL for Groundwater levels.

	Period	Source	Station	Resolution	Application	Chapters
Rainfall	1985-2015	Met Eireann	Mellifont	Daily	Sensitivity Analysis PE and SMB	4, 5
T	1985-2015	Met Eireann	Dublin Airport	Daily	PE and SMB	5
PE	1985-2015	Met Eireann	Dublin Airport	Daily	Sensitivity Analysis PE and SMB	4, 5
Rainfall	2010-2018	Met Eireann	Dunsany	Hourly	Recharge Characterisation Climate Variability and GWL NARX implementation	6, 7, 8
T	2010-2018	Met Eireann	Dunsany	Hourly	NARX implementation Climate Change impacts assessment	8, 9
PE	2010-2018	Met Eireann	Dunsany	Hourly	Recharge Characterisation NARX implementation	6, 8
Rainfall	2011-2012	O'Brien (2013)	Mattock headwaters	15 min	NAM implementation	6
Dischar	2011-2018	EPA	Berril's Farm	15 min	Recharge Characterisation	6
GWL	2008-2018	EPA	MK1, MK2, MK3	15min	Recharge Characterisation Climate Variability and GWL NARX implementation Climate Change impacts assessment	6, 7, 8, 9, 10

3.2.3 Dripsey

The Dripsey study catchment, a tributary of the river Lee, is located in Co. Cork, about 12 km west of Cork city. The catchment is approximately 82 km² in area from the headwaters to the catchment outlet in the Taiscumar reservoir. At this point, the catchment is at a height of about 50 mOD and rises to a height of 434 mOD at its northern limit, as shown in Figure 3.5. The figure also shows the location of the three water level monitoring points: DR1, DR2 and DR3.

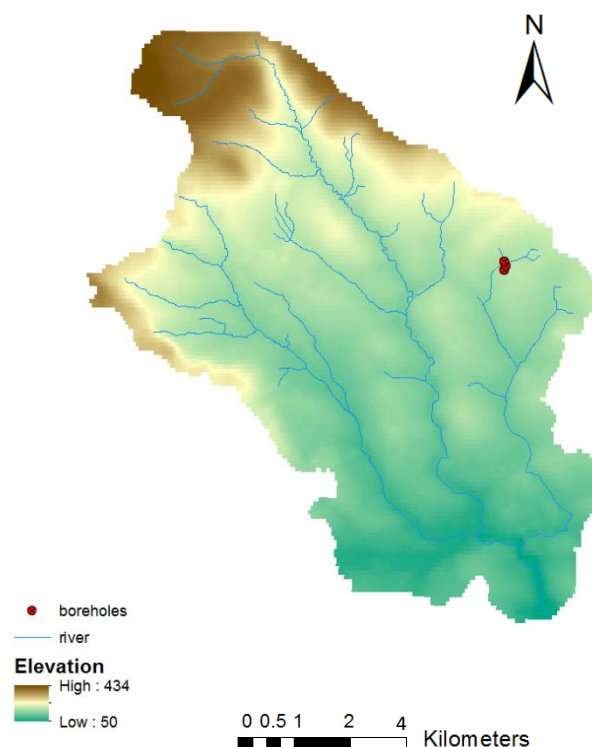


Figure 3.5: Digital elevation model of the Dripsey catchment showing the topography of the study area. The river is represented in blue and the groundwater monitoring points are represented by red dots.

3.2.3.1 Catchment characteristics

The main land use over the catchment is pasture (87.3%) with mixed forest (11.1%), 1.5% under arable cultivation, and just 0.01 % urban or made ground according to the GIS analysis performed using the EPA dataset on land-use. The catchment is mainly covered by well drained soils with patches of peat on the borders of the catchment and alluvium around the river. In addition, there is a significant area at the top of the catchment that is covered by peat. Table 3.2 summarises the types of soil present in the catchment; most of these soils overlie glacial tills derived from the Devonian sandstones, but there are also some bedrock outcrops at the borders

of the catchment, peat on the upper slopes, and some patches of glaciofluvial sands and gravels across the catchment.

Table 3.2 Synthesis of the types of soils in the catchment.

<i>IFS Description</i>	<i>IFS_code</i>	<i>Soil</i>
Deep well drained mineral (derived from non-calcareous)	11	Acid brown earths Brown Podzolics
Shallow well drained mineral (derived from mainly non-calcareous parent materials)	21	Shallow Acid Brown Earths/Brown Podzolics Lithosols Regosols
Deep poorly drained mineral (derived from mainly non-calcareous parent materials)	31	Surface water Gleys Ground water Gleys
Shallow poorly drained mineral (derived from mainly non-calcareous parent materials)	33	Surface water Gleys (Shallow) Ground water Gleys (Shallow)
Poorly drained mineral soils with peaty topsoil (derived from mainly non-calcareous parent material)	41	Peaty Gleys
Shallow, lithosolic or podzolic type soils potentially with peaty topsoil		Podzols (Peaty)
Predominantly shallow soils (derived from non-calcareous rock or gravels with/without peaty surface horizon)	43	Lithosols Peats
Mineral alluvium	51	Variable
Blanket peat	63	Blanket Peats
Made	74	Made

The bedrock is composed of Devonian Old Red Sandstone formations: most of the study catchment is underlain by purple mudstones and sandstones of the Ballytransa Formation, and sandstone and siltstone of the Gyleen Formation at the southern boundary. However, at the centre of the catchment, there are two strips of sandstones and siltstones belonging to the

Gortanimill Formation which indicate the presence of regional scale fractures with a NW-SE orientation (Figure 3.6)

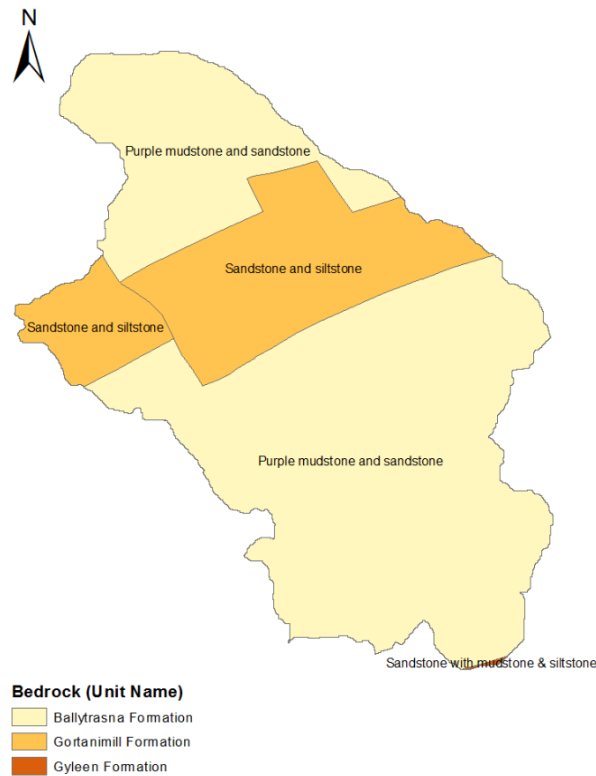


Figure 3.6: Bedrock map of the Dripsey catchment. The different formations constituting the bedrock of the catchment are presented in different colours according to the legend below. The structural features are represented by black lines (Data Source: GSI bedrock mapping).

3.2.3.2 Hydrology and Hydrogeology

The average annual rainfall over the Dripsey is 1328 mm and the mean potential evapotranspiration is 502 mm according to data obtained from the Cork synoptic station (Met Eireann) for the study period (2012-2015). The average estimated actual evapotranspiration is 455 mm which represents 91% of the PE and, consequently, the effective rainfall for this period is about 873 mm per year. The mean annual discharge observed at the outlet during the same period is 777 mm. This disagreement between discharge and effective rainfall could be due to errors in the discharge calculation from the stage discharge curve given that this curve was inferred from few observations (see available data below).

The groundwater vulnerability of the catchment is mainly rated as High, with areas of Extreme vulnerability around the outcrops and at the top of the catchment. The aquifers formed by the

Devonian Sandstones are regarded as Moderately Productive only in Local Zones (LI) which, according to the GSI classification, have a recharge cap of 200 mm/y.

3.2.3.3 Conceptual model

The Dripsey presents all the distinctive features of Poorly Productive Aquifers, in terms of structural and hydrogeological characteristics. The aquifer is covered by thin and dry subsoils, overlying a well-developed transition zone (TZ) that has been proven to be able to transmit water (CDM and OCM 2010b). The boreholes in the area reveal deep weathering of the bedrock that can reach 15 m below the ground. The bedrock has sub-vertical bedding that coincides with the main fractures. These sub-vertical discontinuities are believed to be preferential infiltration pathways towards the bedrock and would be key for the groundwater recharge processes within the aquifer (Figure 3.7).

The EPA/GSI report on this catchment indicates groundwater flow from the upper areas of the catchment towards the river, where there is an upward hydraulic gradient from the deep to shallow bedrock (CDM and OCM 2010b). This report also highlights the heterogeneity and variability of the hydrogeology over relatively short distances.

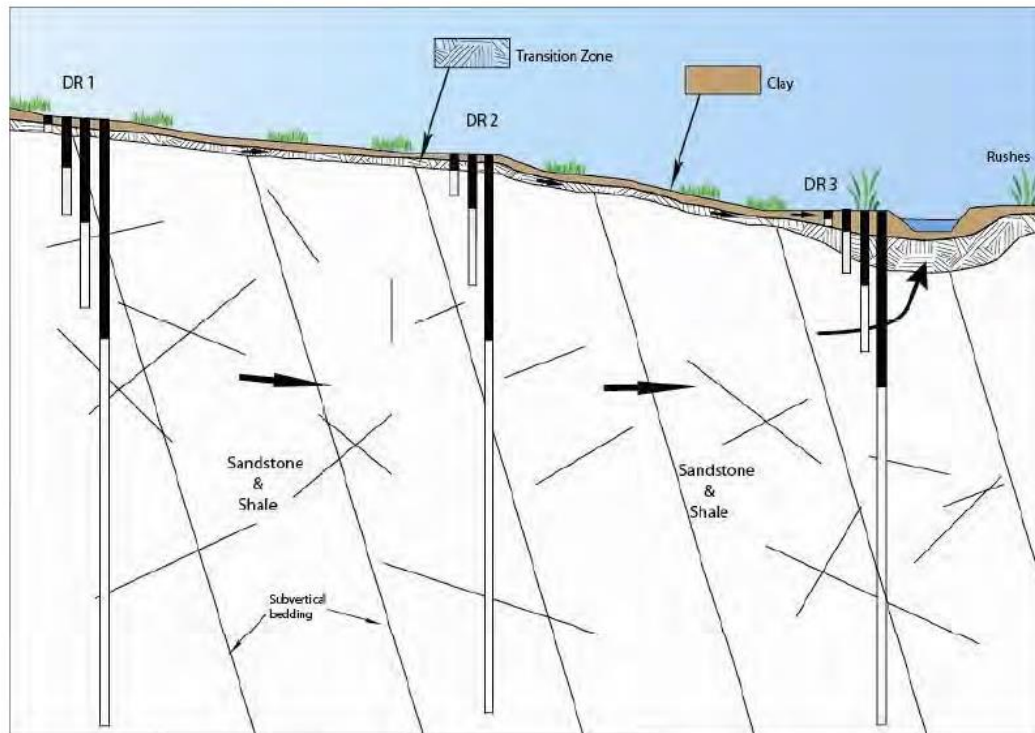


Figure 6: Conceptual Cross Section of the Dripsey Catchment

Figure 3.7: Summary conceptual model of the Dripsey catchment. The cross section presents the location of the three monitoring clusters and the depths of the measurement wells. It also shows the main hydrogeological features of the catchment, inferred from observations on the study area. Source: (CDM and OCM 2010b)

3.2.3.4 Available Data

Similar to the Mattock catchment, the Dripsey was also included in the PPAs project conducted by the EPA. Hence, there are three clusters of boreholes monitoring groundwater levels at 15 minutes resolution from 2008 up to the present time. The datasets were cleaned and de-noised with the same procedure as for the Mattock (Section 3.2.2.4). In this case data from boreholes DR1-TZ and DR3-deep could not be used due to long periods of missing data.

In the Dripsey, there is one hydrometric station owned by the Electricity Supply Board (ESB), just outside the Model Village, about 2.5 km before the river outlet in the Taiscumar reservoir. This station measures the river stage, so the development of a rating curve was necessary (Figure 3.8). ESB provided sporadic stage-discharge measurements from the mid 80's to 2009 which have been used to build the rating curve.

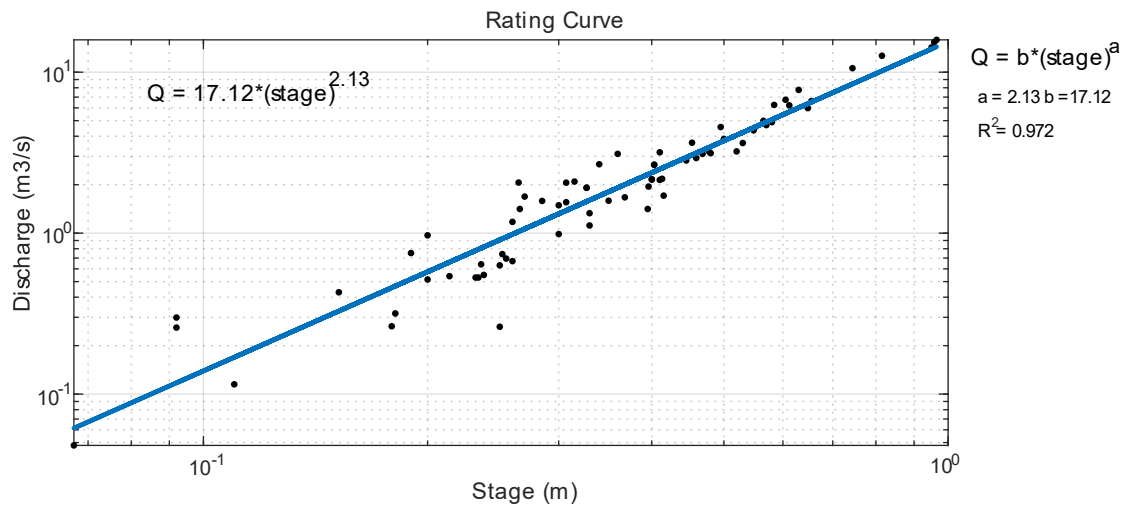


Figure 3.8: Dripsey rating curve with the associated fitted coefficients (a and b) and goodness of fit (R^2).

All the meteorological data used for this study area (rainfall, PE and temperature) were obtained from the Cork Airport station, located 18 km away approximately. Because this station has been active since 1961, and there are long-term hourly resolution datasets, there was no need to complement these datasets with data from other meteorological stations (Table 3.3).

Table 3.3: Summary of the available datasets for the Dripsey catchment and their application throughout the manuscript. T stands for Temperature, PE for Potential Evapotranspiration, SMB for Soil Moisture Budget and GWL for Groundwater levels

	Period	Source	Station	Resolution	Application	Chapters
Rainfall	1985-2018	Met Eireann	Cork Airport	Hourly	Sensitivity Analysis	All (4 onwards)
					PE and SMB Recharge Characterisation Climate Variability and GWL NARX implementation Climate Change impacts assessment	
T	1985-2018	Met Eireann	Cork Airport	Hourly	PE and SMB NARX implementation Climate Change impacts assessment	5, 8, 9
PE	1985-2018	Met Eireann	Cork Airport	Hourly	Sensitivity Analysis PE and SMB Recharge Characterisation NARX implementation	4, 5, 6, 8
Stage Discharge	1982-2009	ESB	Dripsey	Sporadic	Rating Curve	3
Discharge	2012-2015	Calculated	Dripsey	Daily	Recharge Characterisation	6
GWL	2008-2018	EPA	DR1, DR2, DR3	15min	Recharge Characterisation Climate Variability and GWL NARX implementation Climate Change impacts assessment	6, 7, 8, 9, 10

3.2.4 Nuenna Catchment

The Nuenna catchment is located in Co. Kilkenny, and its outlet is about 1km upstream of Freshford town. The Nuenna river, a tributary of the River Nore, has an approximate length of 6.6 km from the headwaters to the outlet, which is called Monument Weir. The contributing drainage area delineates the boundaries of the hydrological catchment, which has an extent of 35 km². The catchment is divided upstream into two further subcatchments, namely the Rocky Weir and the Castle Weir. However, this subdivision is not used in this study. Figure 3.9 shows a steep topographic gradient from the headwaters, where the maximum elevation is approximately 340 mOD, to the outlet which is at 86 mOD.

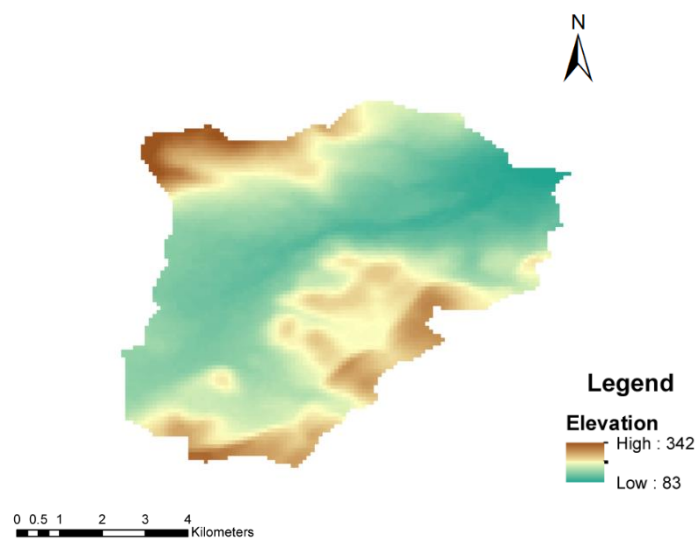


Figure 3.9: Digital elevation model of the Nuenna catchment showing the topography of the study area.

3.2.4.1 Catchment characteristics

According to the GIS analysis carried out, the primary land-use within the catchment is pasture, which represents about 78 % of the area. The rest of the area is used for arable and cultivates (15%), and forests (7%). The percentage of urban or made ground is negligible as there are few rural settlements scattered across the catchment. The study area is predominantly covered by well-drained soils, except for the presence of alluvium next to the watercourse, and small areas of poorly drained soils in the upper catchment where Namurian shales outcrop. The predominant subsoils are moderately permeable tills derived from the underlying lithologies, and permeable glaciofluvial sands and gravels with rock outcrop in the higher grounds. The bedrock of this area is composed of Dinatian limestones at the centre, whereas the higher grounds comprise Namurian shales (Figure 3.10). The limestones correspond to the Ballydams

and Clogrenan formations; these are thick-bedded crinoidal limestone which can reach up to 200 m of thickness (Archbold et al. 2013).

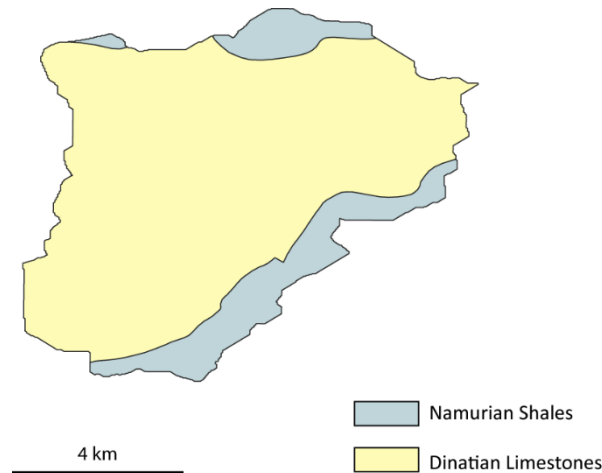


Figure 3.10: Bedrock map of the Nuenna catchment. The different lithologies constituting the bedrock of the catchment are presented in different colours according to the legend below the map

3.2.4.2 Hydrology and Hydrogeology

Average annual rainfall and PE for the catchment are 1088 mm and 543mm respectively during the study period (2012-2015), according to the data obtained from Met Eireann. The Nuenna catchment responds rapidly to large rainfall events, but the recessions are slow and extended. These long recessions are characteristic of catchments underlain by regionally important aquifers and, hence, where the river flow is groundwater-dominated (O'Brien et al. 2013a). In the case of the Nuenna catchment, this is translated into relatively high baseflow indices throughout the year (O'Brien et al. 2013). Groundwater vulnerability ranges from High to X-Extreme according to the GSI mapping. This high vulnerability is due to three main factors: (i) the presence of karst features such as swallow holes; (ii) the bedrock outcrops, or is found in shallow depth in many locations; and (iii) the presence of permeable soils and subsoils as described in Section 3.4.1.

The two main bedrock lithologies constitute aquifers with contrasting characteristics; the Dinatian limestones form karstified aquifers, considered as regionally important (Rkd), where diffuse recharge is dominating, but concentrated (or point source) recharge takes place through the sinkholes and large fractures generated by karstification processes. In contrast, the Namurian shales constitute Poorly Productive aquifers, with reduced diffuse recharge due to the lower permeability of the materials. More specifically, these aquifers are categorised as

Generally Unproductive except for Local Zones (PI) and have an associated recharge cap of 100 mm/y (Hunter Williams et al. 2013)

3.2.4.3 Conceptual Model

The Nuenna is a complex catchment that combines characteristic features of karstic areas (e.g. sinkholes), and some of the distinctive structures of catchments underlain by Poorly Productive Aquifers such as the presence of a Transition Zone (Figure 3.11).

As the higher grounds are formed by the Namurian shales, and covered by a thin layer of till, the infiltration within the headwaters is relatively low. However, the shales contribute indirectly to the recharge processes as the generated runoff flows towards the centre of the catchment, composed by limestones, where both diffuse and allogenic recharge takes place. The Transition Zone, formed by highly weathered limestones, is discontinuous through the catchment. Similar to the Mattock and the Dripsey, the groundwater levels are monitored within the catchment by EPA boreholes. There are two clusters of boreholes, the analysis of which confirm this conceptual model and allowed estimates of transmissivity between 0.3 m²/day to 2.6 m²/day through pumping tests (Archbold et al. 2015). However, it must be noticed that these low transmissivity values are not representative of the conduit flow character of much of the limestone.

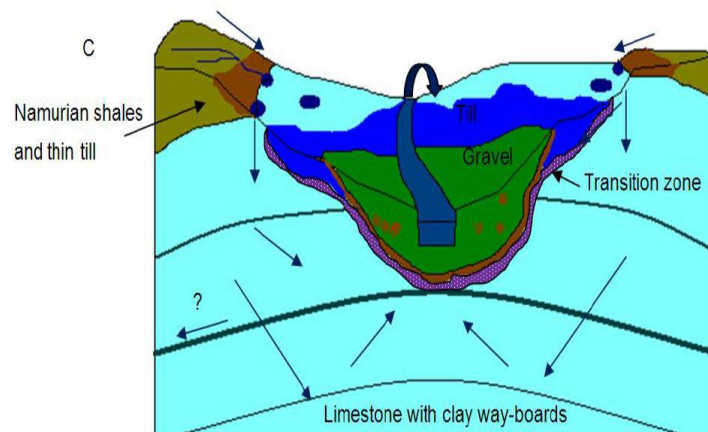


Figure 3.11: Conceptual model of the Nuenna catchment. Source: Archbold and Deakin, (2011).

3.2.4.4 Available Data

As mentioned in the Introduction to this chapter, the Nuenna catchment was studied only in the early stages of this project, for comparison purposes during the sensitivity analysis between a regionally important aquifer with a poorly productive aquifer (see Section 3.2.1). For this reason,

neither discharge nor groundwater level data were required, even though the catchment is instrumented by the EPA. All the hydrometeorological data needed (rainfall, PE, temperature) were obtained from the Kilkenny synoptic station for the 1985-2015 period (Table 3.4).

Table 3.4: Summary of the available datasets for the Nuenna catchment and their application throughout the manuscript. T stands for Temperature, PE for Potential Evapotranspiration and SMB for Soil Moisture Budget.

	Period	Source	Station	Resolution	Application	Chapters
Rainfall	1985-2018	Met Eireann	Kilkenny	Daily	Sensitivity Analysis PE and SMB	4, 5
T	1985-2018	Met Eireann	Kilkenny	Daily	PE and SMB	5
PE	1985-2018	Met Eireann	Kilkenny	Daily	Sensitivity Analysis PE and SMB	4, 5

3.2.5 Additional groundwater data: the Knocktopher borehole site

Chapter 7 examines the effect of large-scale atmospheric and oceanic patterns on low-frequency groundwater levels variability. As presented above, the groundwater level records of the selected study catchments started in 2008 with the EPA project on poorly productive aquifers. As the teleconnection patterns present long periodicities (up to multidecadal), a longer-term dataset was required to put into broader context the results obtained for the Mattock and the Dripsey. After a thorough examination of the groundwater level records in Ireland, the Knocktopher dataset was selected as it starts 1980. The Knocktopher borehole is located within the village of Knocktopher in Co. Kilkenny, on early Dinantian sandstones, shales and limestones, which according to the GSI constitute Moderately Productive only in Local Zones (LI) with an associated recharge cap of 200 mm/y and corresponds to the groundwater body of Clifden south.

However, the time series presents some long and frequent discontinuities that could not be reconstructed by simple interpolation methods and, therefore, just data from 1995 onwards has

been used. The groundwater levels have been compared with rainfall and temperature data obtained from the Kilkenny synoptic station (Table 3.4), which is about 8 km away.

3.3 Infiltration Capacity Study Sites

3.3.1 Introduction

This section describes the research study sites that were used to study the infiltration capacity. Sections 3.2.2 and 3.2.3 summarise the Crecora and Kilmallock sites, respectively (Figure 3.12). In each section, the location and hydrogeological characteristics of the site are presented as well as the instrumentation installed. These study sites were part of another PhD project carried out in collaboration between Trinity College Dublin and University of Limerick (Knappe 2019).

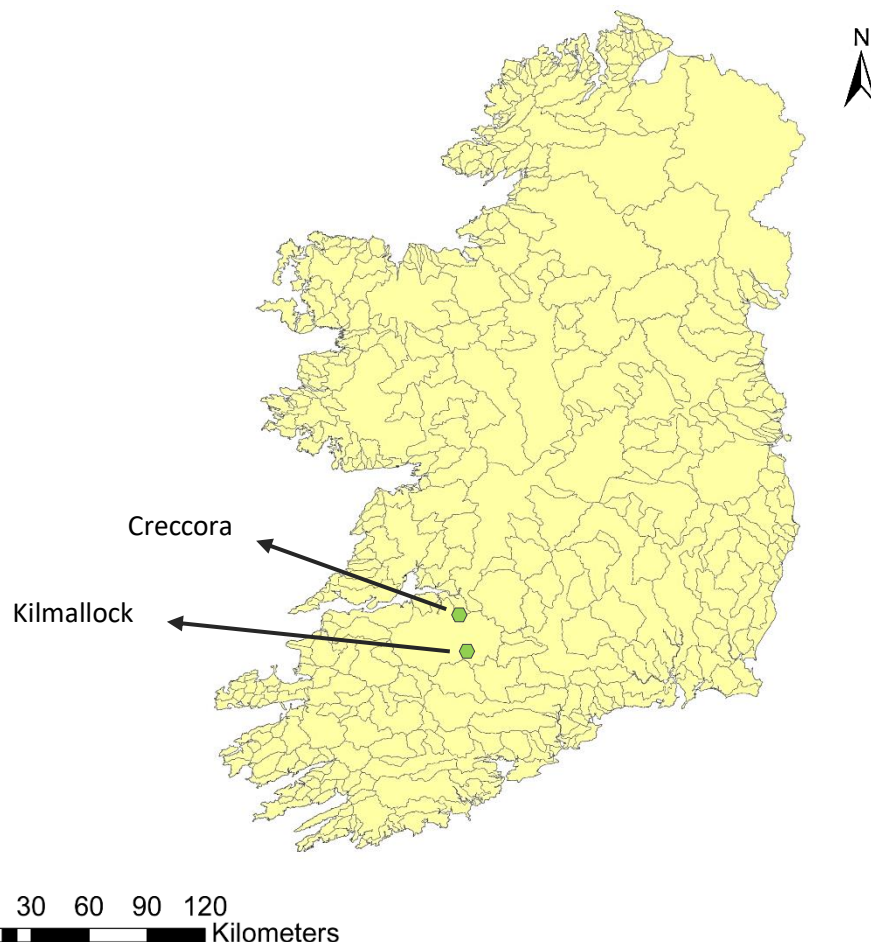


Figure 3.12: Localisation of the two infiltration sites (green pentagons).

3.3.1.1 Crecora Site

Crecora is a village located in County Limerick, about 13km away from Limerick city itself (Figure 3.13); the study site is located approximately 2.6 km from Crecora town.

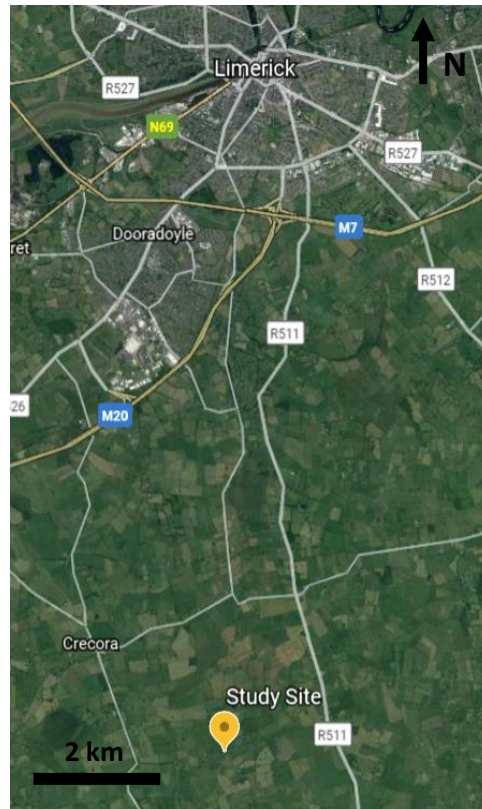


Figure 3.13: Location of the Creccora study site

The bedrock at this location is formed by massive unbedded Walusortion limestones (Carboniferous), which constitute a Regionally important karstified aquifer (Rkd). The overlying subsoils are tills derived from the limestones, with moderate permeability. Following the GSI classification, the site has a High groundwater vulnerability. Additionally, according to the National Recharge Map (Hunter Williams et al. 2013), this study site has a recharge coefficient of 60%, and annual average groundwater recharge of 143 mm/y with no recharge cap associated.

a) Site Instrumentation and Data

This study site was instrumented with a weather station, which monitored rainfall, temperature, net radiation and wind speed for the 4 years duration of the corresponding PhD project. These data were then used to estimate PE with the Penman-Monteith equation, which was an input for the unsaturated zone modelling (Chapter 5). The site was also equipped with a soil moisture sensor (EC5-sensor) to monitor the volumetric water content at different depths (10 cm, 25 cm,

50 cm, 75 cm, 100 cm and 125 cm depth). Sporadic measurements of the groundwater level within the study site suggest that the water table depth is less than 2.7m below ground level (Table 3.5).

Table 3.5: Synthesis of the data available for the Creccora site and its application. PE stands for Potential Evapotranspiration, Θ indicates volumetric water content within the soil and GWL groundwater levels.

	Period	Resolution	Application	Chapters
Rainfall	Jun 2016- Dec 2018	Hourly	Infiltration Capacity	5
PE	Jun 2016- Dec 2018	Hourly	Infiltration Capacity	5
Θ	Jun 2016- Dec 2018	Hourly (5 Depths)	Infiltration Capacity	5
GWL	-	Sporadic	Infiltration Capacity	5

Additionally, three soil samples taken at depths of 75, 100 and 150 cm were analysed in order to obtain the textural classification of the soils. According to the UK SSEW (RDS,2006), the soils at this location correspond to a clay loam and sandy loam.

3.3.1.2 Kilmallock Study Site

Kilmallock is a town on the southern border of Co. Limerick with Co. Cork. The study site is at the southeaster edge of the town (Figure 3.14).



Figure 3.14: Location of the Creccora study site

The bedrock geology in this area is formed by the Clogrennan formation, belonging to the Visean limestones. These Carboniferous limestones are massive crinoidal and cherty limestones, with local algal laminations. From the hydrogeological point of view, these materials constitute Locally important aquifers (LI) which have an associated recharge cap of 200 mm/y. The overburden consists of tills derived from the limestones with a moderate permeability and a corresponding recharge coefficient of 60% according to the national recharge map, similar to the Creccora study site. In contrast, the groundwater vulnerability in this area is regarded as moderate rather than high as it is at the Creccora site.

b) Site Instrumentation and Data

Similar to the Creccora site, this location was equipped with a weather station which automatically collected hourly measurements of rainfall, temperature, wind speed, barometric pressure and net radiation for the 4-year duration of the PhD project. The continuous monitoring of these climate variables allowed the estimation of PE by applying the Penman-Monteith equation. Soil moisture volumetric content was also monitored with a soil moisture sensor (EC5-sensor) at ground surface and 5 cm and 50 cm depth (Table 3.6). Groundwater level measurements suggest that the water table depth is about 1.6 m below the surface. Soil samples

taken at 75, 100 and 150 cm depth for particle size analysis allowed the classification of the soil as a Sandy Loam according to UK SSEW (RDS, 2006).

Table 3.6: Synthesis of the data available for the Kilmallock site and its application. PE stands for Potential Evapotranspiration, Θ indicates volumetric water content within the soil and GWL groundwater levels.

	Period	Resolution	Application	Chapters
Rainfall	Nov 2015- Nov 2017	Hourly	Infiltration Capacity	5
PE	Nov 2015- Nov 2017	Hourly	Infiltration Capacity	5
Θ	Nov 2015- Nov 2017	Hourly (3 Depths)	Infiltration Capacity	5
GWL	-	Sporadic	Infiltration Capacity	5

4. Groundwater Recharge Sensitivity Analysis

4.1. Introduction

As well as meteorological factors, the geological properties of a region also influence groundwater recharge rates. As discussed in Chapter 2, there are two main geological features that limit groundwater recharge in Ireland. Firstly, a significant part of the island is covered by glacial tills, so the permeability and thickness of this type of subsoil are major controls on the infiltration rates to the underlying bedrock aquifers. Secondly, two thirds of the country are underlain by aquifers classified as 'Poorly Productive'. In these aquifers, groundwater flow is constrained by the properties of the fracture network which results in a limited throughput and storage capacity.

These characteristics have underpinned the recharge estimation methods applied. In Ireland, groundwater recharge calculations have been typically based on a combination of soil water-budget techniques and river base-flow analysis. The water-budget techniques are based on estimates of effective rainfall (which is defined as the difference between rainfall and actual evapotranspiration) using a soil moisture deficit approach. Afterwards, recharge coefficients are applied in order to represent the percentage of water that reaches the water table and becomes actual recharge. These coefficients depend on a number of variables such as the aquifer type, soil drainage, but especially subsoil permeability and thickness. This methodology has proven useful providing first estimations of groundwater recharge, and it led to the development of the national recharge map based on a GIS-based tool that has been used in this analysis (Misstear et al. 2009a; Hunter Williams et al. 2013).

The anticipated changes in both rainfall and temperature (see Chapter 2) are expected to have an impact on the hydrological cycle by intensifying it. Most of the existing climate impact studies in groundwater are at catchment scale, since it helps to simplify the groundwater estimations as catchments can be treated as independent systems with defined properties. Some relevant properties such as permeability, porosity or the presence of fractures, have an important controlling effect on the amount of water that can reach the water table and be stored within the aquifers. Because of that, the response of the aquifers towards possible climate alterations depends on the local settings and, therefore, the magnitude of the impact of climate change depends on the characteristics of each catchment. This is of special importance in Ireland where a significant percentage of the

island is covered by low permeability materials and underlain by low storativity aquifers as discussed in Chapter 2.

The overall purpose of this project is to improve qualitatively and quantitatively our knowledge of how the recharge processes occur in Irish fractured bedrock aquifers and to assess the possible impacts of a changing climate within these type of aquifers (Section 1.3). To achieve these objectives, it is necessary, firstly, to understand the role that bedrock properties play in constraining groundwater recharge, and to then be able to develop a robust conceptual recharge model. In this chapter a first assessment is presented through a sensitivity analysis that considers both hydroclimatic and hydrogeologic characteristics. This analysis has been carried out using the GIS-based tool described in Section 2.1.

4.2. Methods

The sensitivity analysis was carried out in two stages: an initial, simpler analysis at county scale, followed by a second and more detailed analysis at catchment scale. The idea behind performing an initial analysis at county scale is to capture the wide range of hydrogeological settings that exists in Ireland. Hence, it is important that the selected county presents high heterogeneity, from subsoils to aquifers.

The general analysis at county scale included a wide range of hydrogeological and hydrometeorological settings and was applied to County Kildare as it includes poorly productive aquifers, karstic aquifers and Ireland's most extensive sand and gravel aquifer (Figure 4.1). The more specific approach was applied to the groundwater recharge study catchments described in Section 3.2: Mattock, Dripsey and Nuenna (see Figure 3.1).

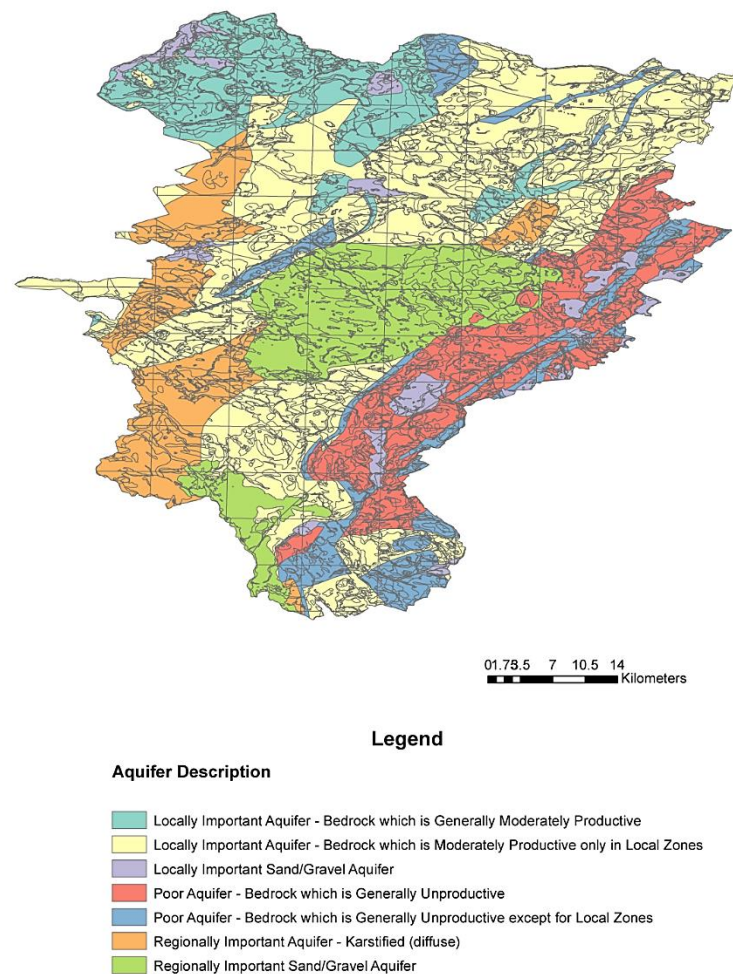


Figure 4.1: Aquifer categories present within Co. Kildare (Data Source: GSI)

Because there is a slight difference in complexity between the two approaches, the procedure was slightly different despite the same concept being applied; a variable was modified while fixing the others, to be able to determine how it constrains groundwater recharge. The larger the variation, the larger is the sensitivity to the studied variable. For a better understanding of the approach in both cases, it is necessary to keep in mind that the GIS tool inputs were annual effective rainfall values. Hence, even though the input variables included in this sensitivity analysis have different temporal resolutions (Table 4.1), the results obtained are always presented as average annual recharge.

In this way, factors controlling potential and actual recharge were examined; the list of variables tested are summarized in Table 4.1. The ranges of variation of the variables included in the sensitivity analysis were established based on existing bibliography and are presented below.

Table 4.1: List of variables included in the sensitivity analysis for potential and actual recharge and its temporal and spatial scale

	Variables	Temporal scale	Spatial scale
Potential Recharge	Rainfall rates	Annual	County
	Rainfall intensity	Daily	Catchment
	Rainfall seasonality	Daily	Catchment
	AE rates	Annual	County
Actual Recharge	Recharge coefficients	[-]	County & Catchment
	Recharge caps	[-]	County & Catchment

4.2.1 Hydrogeological variables: Recharge coefficients and caps

The sensitivity of groundwater recharge to the local hydrogeological settings has been tested in both approaches, the generic and the specific, and so the same range of values have been applied in all cases. The best estimates for the recharge coefficients were established in Hunter Williams *et al.* (2013) when the national recharge map was developed. This followed earlier work describing the results of recharge estimations and recharge coefficients in four study catchments (Misstear *et al.* 2009b). Nevertheless, there is an associated uncertainty with the estimation of these coefficients. In Hunter Williams *et al.* (2013), this uncertainty is represented as a table (see Table 2.2) where a likely range of coefficients is presented for each hydrogeological setting: the minimum and maximum values are intended as the lower and upper bounds of plausible values, and the two limits of the inner range values. Finally, the best estimates (original values, hereinafter) correspond to the average between the higher and lower inner range values. In this sensitivity analysis, the four alternative sets of coefficients defined by Hunter Williams *et al.* (2013) (Table 4.2) have been used to generate four recharge scenarios (see Section 2.1.1) and to compare them to the average recharge calculated with the original values (Figure 4.2).

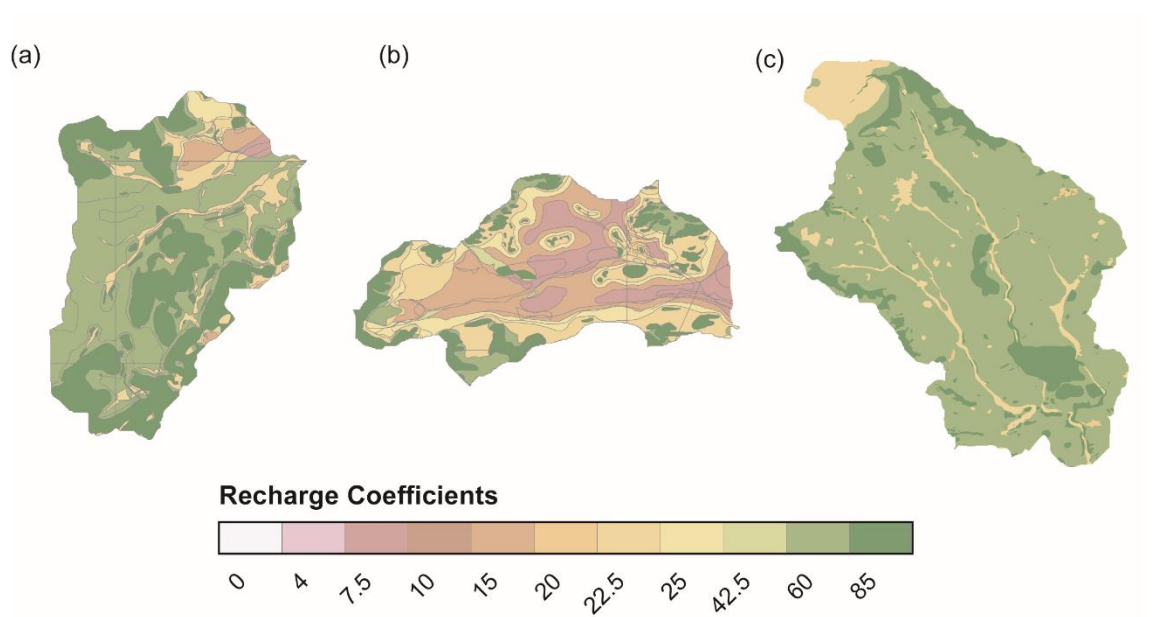


Figure 4.2: Original values of the recharge coefficients extracted from Hunter Williams *et al.*, (2013) for (a) the Nuenna, (b) the Mattock and (c) the Dripsey catchments.

Table 4.2: Sets of recharge coefficients used on the sensitivity analysis from (Hunter Williams et al. 2013). The notation corresponds to that on Table 2.2. X.m represent made soils.

Hydrogeological settings	Originals (%)	Minimum (%)	Lower Inner range (%)	Higher Inner range (%)	Maximum (%)
1.i	85	30	80	90	100
1.ii	85	50	80	90	100
1.iii	42.5	15	35	50	70
1.iv	60	45	50	70	80
1.v	22.5	5	15	30	50
1.vi	85	50	80	90	100
1.vii	22.5	1	15	30	50
2.i	85	50	80	90	100
2.ii	85	50	80	90	100
2.iii	42.5	15	35	50	70
2.iv	42.5	15	35	50	70
2.v	60	35	50	70	80
2.vi	22.5	10	15	30	50
2.vii	25	1	20	30	40
2.viii	10	1	5	15	20
3.i	60	35	50	70	80
3.ii	22.5	10	15	30	50
3.iii	15	1	10	20	30
3.iv	4	1	3	5	10
4.i	7.5	1	5	10	20
4.ii	4	1	3	5	10
5.i	85	30	80	90	100
5.ii	60	35	50	70	80
5.iii	22.5	10	15	30	50
5.iv	7.5	1	5	10	20
5.v	5	1	1	5	20
X.m	20	20	20	20	20

Regarding the recharge caps, similar information can be inferred from the existing literature such as Comte et al. (2012) and Tedd et al. (2012). It was decided to modify the values by decreasing and increasing the values of the recharge caps by 50 mm/y and 25 mm/y, as shown in Table 4.3. In this case, a fifth scenario was generated to simulate the absence of recharge caps. In order to do that, the caps have been set to 1000 mm/year (i.e. in excess of the effective rainfall for the study areas) to nullify their effect.

Table 4.3: Cap values used in the sensitivity test for aquifers regarded as Locally Important Aquifer - Bedrock which is Moderately Productive only in Local Zones (LI), Poor Aquifer - Bedrock which is Generally Unproductive except for Local Zones (PI), and Poor Aquifer - Bedrock which is Generally Unproductive (Pu)

Name	Variation	CAP (LI)	CAP (PI, Pu)
Low	-50 mm/year	150	50
Low-medium	-25 mm/year	175	75
Medium –High	+ 25mm/year	225	125
High	+50 mm/year	250	150

4.2.2 Hydrometeorological variables

The modification of all the hydroclimatic series was performed according to the anticipated changes in the Irish climate, described in Gleeson et al. (2013) and IPCC et al. (2013), for both the generic and specific approach. In the case of the generic approach, both AE and rainfall annual rates were modified to simulate 5%, 10% and 20% increases and decreases. Because there is an existing rainfall grid for Ireland with a good resolution, this was directly used to simulate the rainfall variability. However, this is not the case for actual evapotranspiration, for which there are just contour maps available. Therefore, actual evapotranspiration for Co. Kildare was interpolated from the available contours as a baseline and using a spline technique. Note that because of this interpolation process, the effective rainfall values differ from the original dataset leading to differences in recharge outputs of about 5 mm /y between the calculated and the original dataset. Once the grid of AE over Co Kildare was calculated, new grids were generated by multiplying the annual values by the desired rate of change.

As we have noted, climate projections for rainfall anticipate an increase in rainfall intensity and also an amplification of seasonality. For this reason, groundwater recharge sensitivity to these variables has been investigated in the specific approach. To do this, historical rainfall and potential evapotranspiration (PE) daily series were obtained from Met Eireann for a period of 30 years (1985-2015) for the three selected catchments: Mattock, Dripsey and Nuenna. Precipitation series were from the closest rainfall station with available data over the period. Similarly, potential evapotranspiration data came from the closest synoptic station to each one of the catchments (see Section 3.2.1).

To summarize, lumped daily rainfall data and PE estimations have been used as input. Actual evapotranspiration (AE) estimations have been calculated by a soil moisture budget approach, following the recommendations of the Food and Agriculture Organization of the United Nations (FAO), and combining it with land use information from the EPA, so AE estimations are distributed. This made it possible to calculate effective rainfall also in a distributed way and use it as an input for the GIS tool (Figure 4.3).

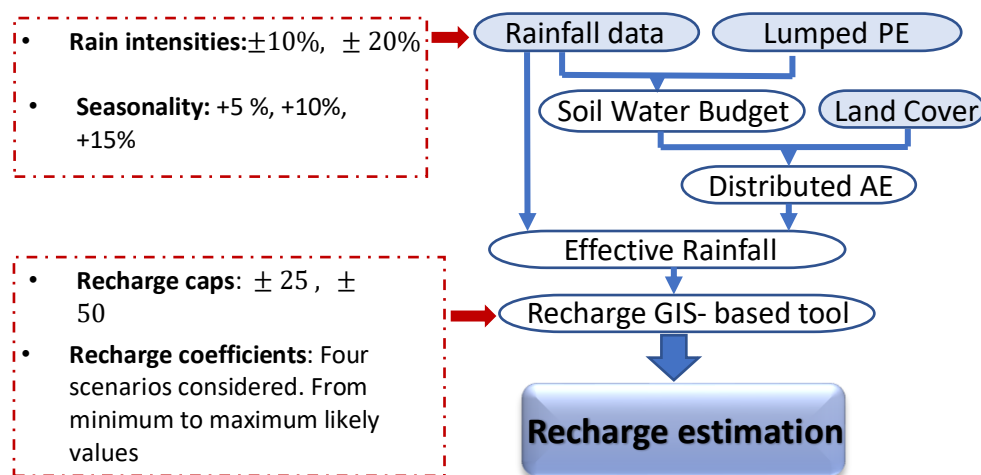


Figure 4.3: Flow chart of the methodology applied in the sensitivity analysis.

As represented in Figure 4.3, the GIS tool includes land cover information to calculate AE from PE following the FAO methodology. It must be noted that, with the ongoing global change and expected increase of population, it is extremely likely that land use and cover of Irish rural areas will be highly altered in the future (i.e. increased areas of reduced permeability owing to urbanisation, housing, road construction etc). This would in turn have a significant effect on groundwater resources. Nevertheless, these impacts fall into the

category of “indirect” impacts according to Taylor et al. (2013), which are beyond the scope of this research project.

The manipulation of the rainfall was performed with the statistical downscaling method decision- centric (SDSM-DC) software (Wilby et al. 2002, 2014) on a daily basis. The modification of rainfall intensity was achieved by preserving the annual totals and altering the percentage of occurrence of rain days. The addition and removal process of rain days was done by a stochastic forcing, which is based on the existing likelihood of events in each month. In this way, wetter months have a greater chance to have a rainy day added and vice versa. The increment of intensity was done by removing wet days so, to preserve the total, the intensity of the remaining days needed to be higher. Four new precipitation scenarios were generated: two in which rainfall intensity was incremented by 10% and 20%, and two more in which the intensity was reduced by the same percentages.

The alteration of the rainfall seasonality was done in a similar manner to that presented above for rainfall intensity: by fixing the annual averages, then increasing the number of wet days for the winter months (December, January and February), and reducing the number in the summer months (June, July and August), by a set percentage in each case.

4.3 Results

4.3.1 General approach: County Scale

The aim of the sensitivity analysis at county scale was to obtain a first general idea of the system and the relationship between the main controlling variables. In this way, an initial simple analysis was performed for County Kildare. This initial test included the sensitivity to recharge caps and coefficients, but also changes in rainfall and actual evapotranspiration rates.

4.3.1.1 Recharge Coefficients

The range of likely recharge coefficients values presented by Hunter Williams et al (2013) were used to generate four new recharge scenarios: (1) minimum likely value, (2) lower limit of the inner range, (3) higher value of the inner range and (4) maximum.

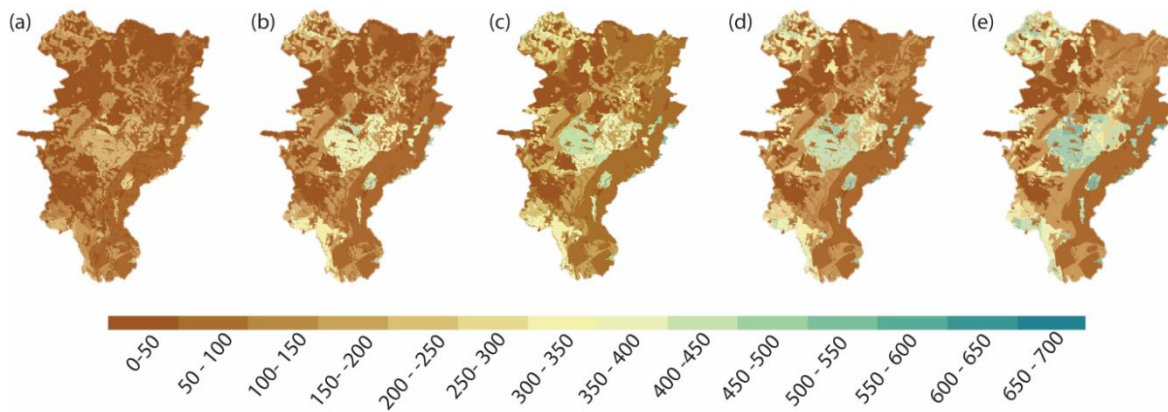


Figure 4.4: Recharge scenarios in Co. Kildare generated from the five recharge coefficient sets: (a) Minimum (b) Lower inner range (c) Original values (d) Higher inner range (e) Maximum

As expected, the results show a direct relationship between the recharge coefficients and groundwater recharge: the higher the coefficients, the higher the recharge (Figure 4.4). It can also be seen that there are some areas more sensitive than others: high sensitivity areas (more variable) correspond to those zones with high recharge rates, either because the infiltration rates are high, or because they are not affected by recharge caps (Figure 4.5). In fact, the results also suggest that the less sensitive areas are those corresponding to poorly productive aquifers since recharge cannot increase in these areas once the threshold set by the cap is reached.

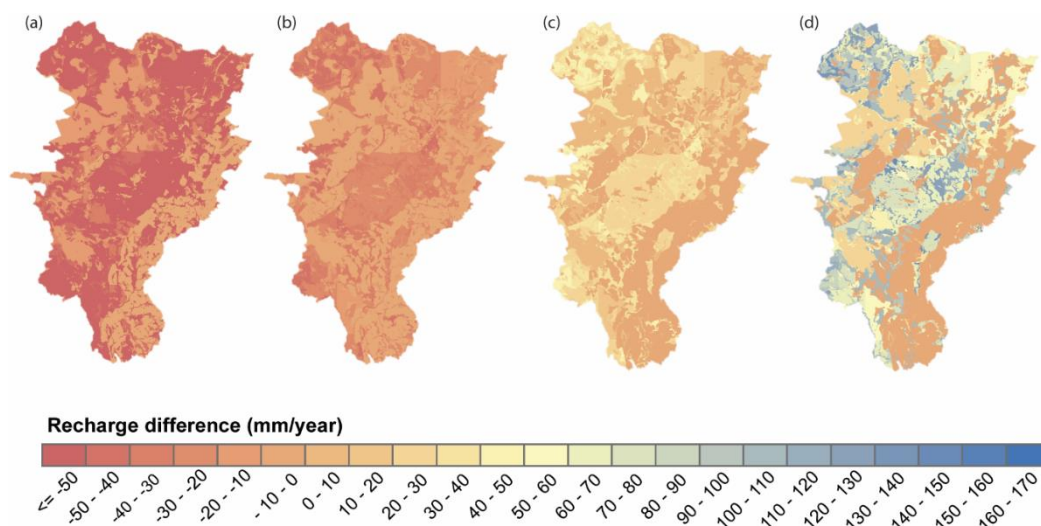


Figure 4.5: Difference in annual recharge between the original recharge map and the four new scenarios generated; (a) Minimum (b) Lower inner range (c) Higher inner range (d) Maximum

4.3.1.2 Recharge Caps

The recharge cap values have been modified to simulate an increase and decrease in the storage capacity of the aquifers by 50 mm/y and 25 mm/y. In this case, a fifth scenario was also generated to simulate the absence of recharge caps. In order to do that, the caps have been set to a value above the effective rainfall (1000 mm/year was chosen as this high value) to nullify their effect.

The first thing that can be observed in the output maps is that only the areas that are underlain by PPAs are sensitive to these changes (Figure 4.6).

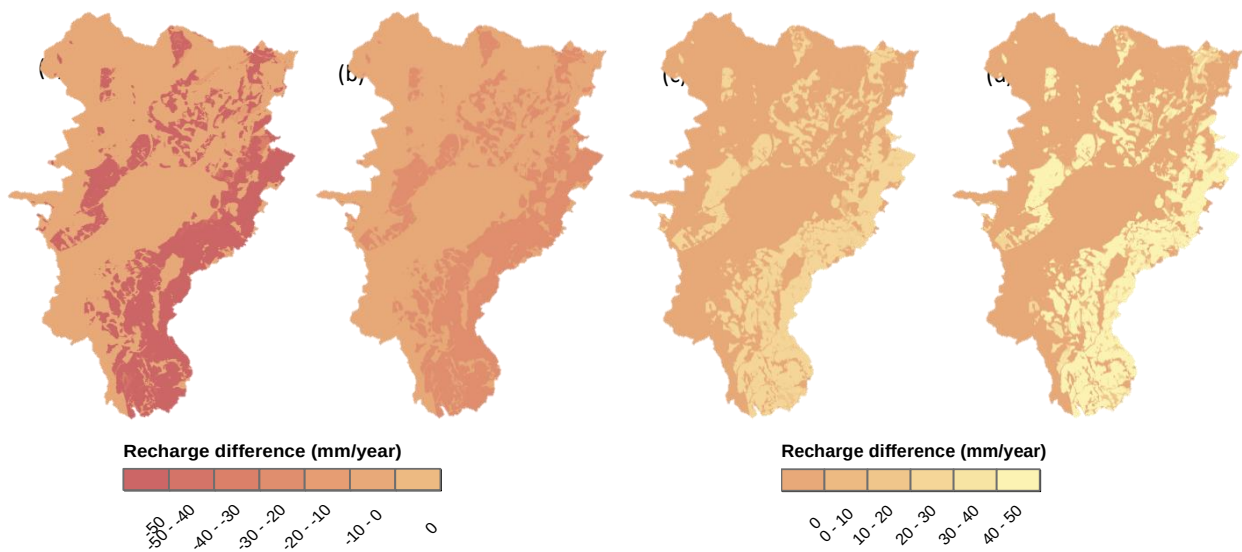


Figure 4.6.: Difference in annual recharge for the four scenarios generated from (a) Low recharge cap values (b) Medium-Low cap values, (c) Medium-High cap values and (d) High cap values

Again, a direct relationship between the input variable and the output can be appreciated: the higher the caps, the higher the annual recharge. In addition, the maximum difference in recharge for each point is equal to the change applied to the cap values. However, the results show that modifying the recharge caps does not affect the maximum recharge values, except in the no-caps scenario (Table 4.4). This can be explained by the fact that, in Co. Kildare, maximum recharge occurs in areas with high permeability which are not underlain by recharge caps, notably in the central area occupied by the mid-Kildare gravel aquifer. Only in the scenario in which recharge caps are nullified, annual recharge maximum values are enhanced in other areas and surpass the maximum recharge estimated in the original recharge map.

Table 4.4: Recharge estimates (mm/y) obtained for the five scenarios generated over County Kildare.

	Mean Recharge	Maximum
Original map	115	589
	Mean Recharge	Maximum
Low	106	589
Medium-Low	106	589
Medium-High	122	589
High	128	589
No caps	159	783

4.3.1.3 Rainfall rates

Most of recharge calculation methods are based on soil moisture budgeting techniques in which the hydrologically effective rainfall is calculated and then used as an input for the hydrological system (see Section 2.1). For this reason, it is necessary to determine how rainfall amounts and actual evapotranspiration rates influence groundwater recharge.

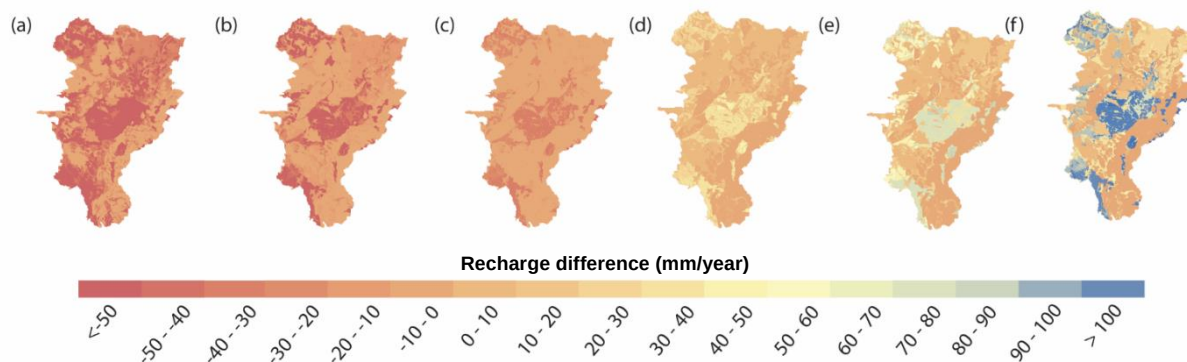


Figure 4.7: Difference in annual recharge (mm/y) for different annual rainfall rates: (a) + 20%, (b) + 10%, (c) + 5%, (d) - 5%, (e) - 10%, (f) - 20%

For this analysis, annual rainfall values were modified to represent an increase in rates of 5%, 10% and 20% and also decreased by the same rates. As expected, recharge shows a direct relationship with annual rainfall and it appears to be slightly more sensitive to increases in rainfall rates. The results shown by the output maps can be easily linked with those obtained previously; the areas with a higher change correspond to those with high recharge coefficients (high subsoil permeability) and not affected by recharge caps (Figure 4.7). In contrast, the less sensitive areas are, as expected, those affected by low recharge caps.

Hence, although an increase in rainfall rates generates a rise in annual recharge rates, this rise is restricted first by the infiltration capacity of the overlying materials and second by the water acceptance capacity of the aquifer.

4.3.1.4 Actual evapotranspiration rates

Similarly to the rainfall rates, annual AE values were increased and decreased by 5%, 10% and 20%. In this case, there is an inverse relationship between both variables, so an increment of the AE annual rates leads to a reduction in recharge. However, the results obtained are similar to the previous ones in terms of the linkages with the variables controlling actual recharge (Figure 4.8). Once more, the areas with a higher change match with the areas with high subsoil permeability and aquifer storage capacity, while the less sensitive areas are those affected by recharge caps.

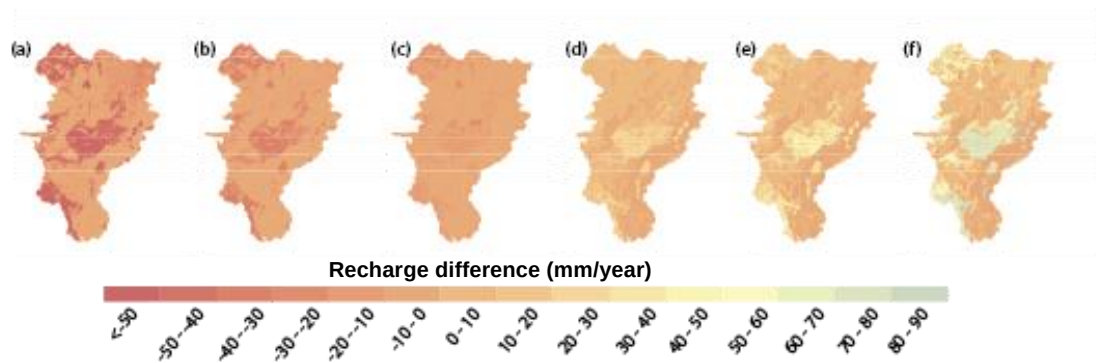


Figure 4.8: Difference in annual recharge (mm/y) in Co. Kildare for different annual AE rates: (a) + 20%, (b) + 10%, (c) + 5%, (d) - 5%, (e) - 10%, (f) - 20%

4.3.2 Specific approach: Catchment Scale

This second part of the sensitivity analysis aimed to assess the influence of the hydrogeological variables at a smaller scale, especially in catchments that are fully underlain by PPAs i.e. where their whole extent is affected by a recharge cap, such as the Mattock and the Dripsey. However, it is important to also analyse the effect on catchments partially underlain by PPAs such as the Nuenna to observe the contrast between aquifers. Additionally, recharge sensitivity to further detailed hydroclimatic variables is explored to emulate likely rainfall changes caused by climate change as anticipated by climate projections.

4.3.2.1 Recharge coefficients

The results obtained for the three selected catchments are consistent with the results presented at county scale. This agreement in results is more apparent in the Nuenna catchment due to its heterogeneity. Thus, the borders of the catchment, affected by recharge caps, present little variation to the changes in recharge coefficients whereas the centre of the catchment exhibits a clear linear relationship as observed earlier (Figure 4.9).

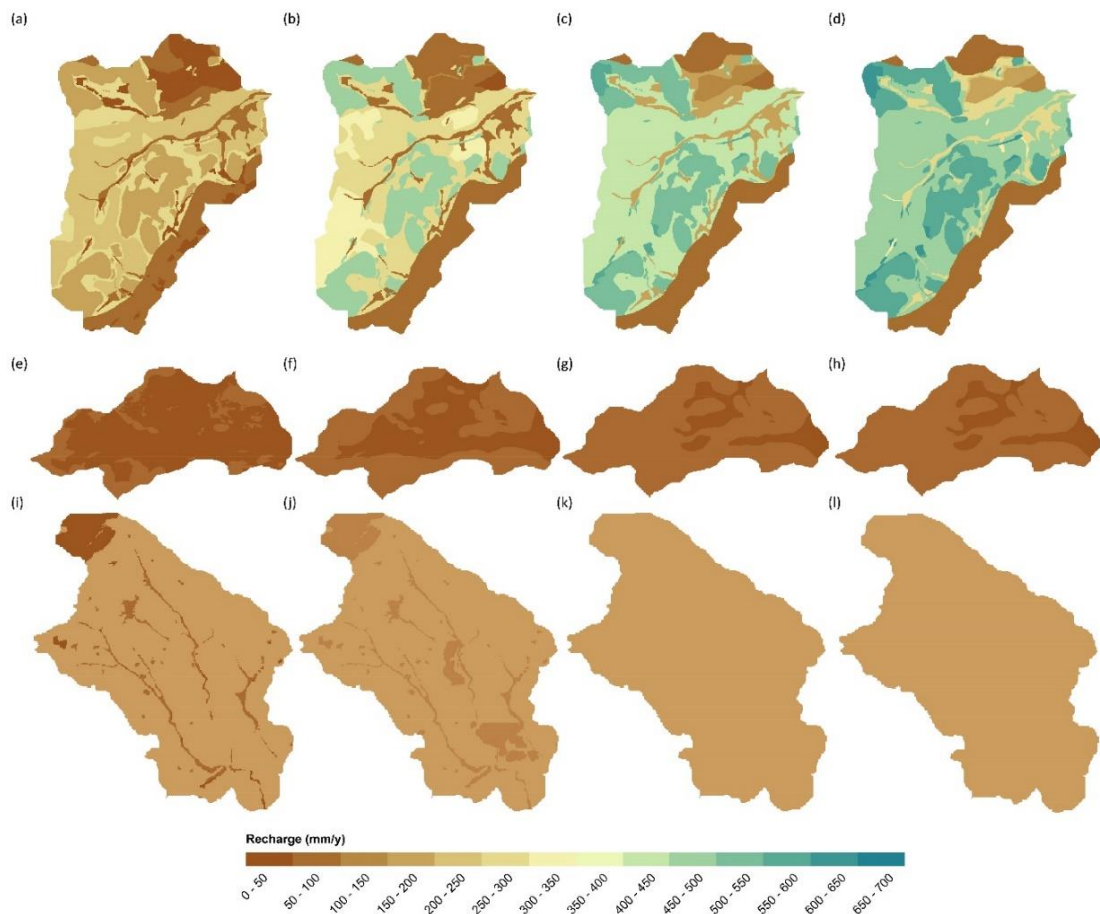


Figure 4.9: Recharge scenarios generated for the Nuenna (a,b,c,d), Mattock (e,f,g,h) and Dripsey (i,j,k,l) considering four sets of recharge coefficients: Minimum (a,e,i), Lower Inner range (b,f,j), High Inner range (c,g,k) and Maximum (d,h,l).

However, in the case of the Mattock and the Dripsey, this relationship is not as obvious due to the control exerted by the recharge caps. Therefore, there is no observable effect caused by increasing the recharge coefficients, as the limited storage capacity of the aquifer restricts further groundwater recharge. Similarly, the response to reduced recharge coefficients is also buffered. Hence, despite the fact that there is a strong linear relationship between

recharge coefficients and groundwater recharge, this linearity is affected by the recharge acceptance capacity of the underlying aquifer.

4.3.2.2 Recharge caps

The evaluation of groundwater recharge sensitivity to the storage capacity of the aquifers (or recharge caps), has also led to consistent results. Again, the results obtained for the Nuenna catchment are more evident and easily relatable to the outcomes presented at county scale. The resulting maps for the Mattock and the Dripsey provide a detailed example of how the recharge caps dominate groundwater recharge within these catchments.

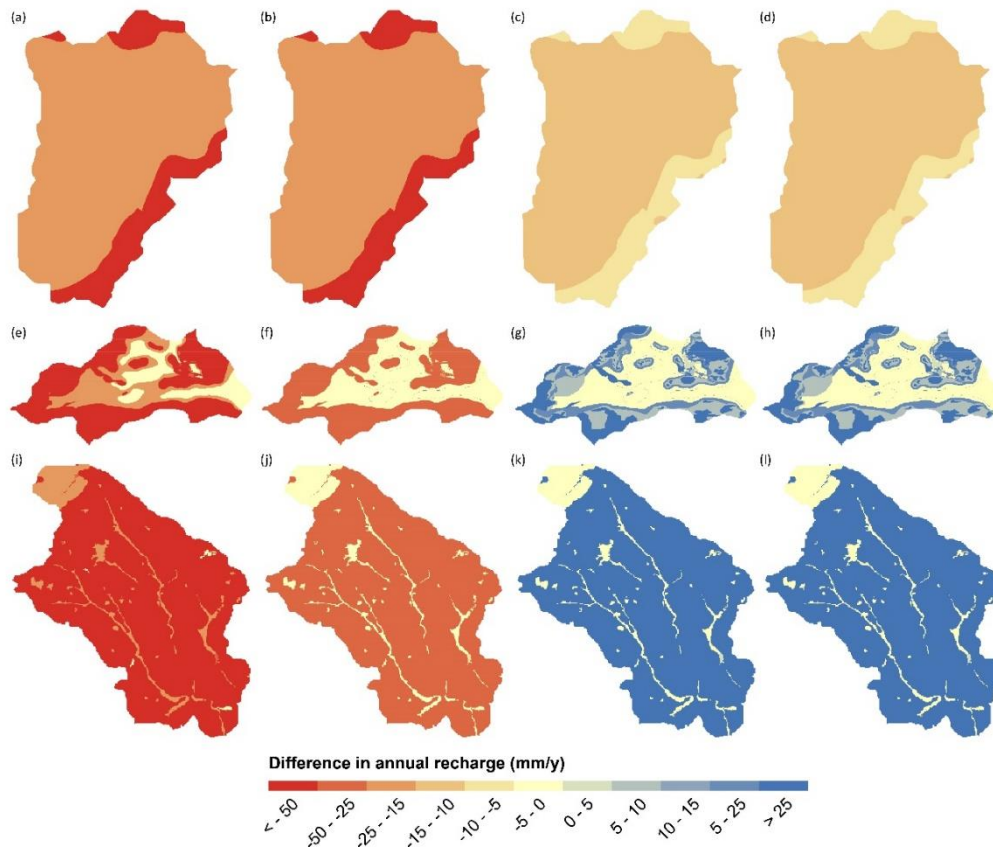


Figure 4.10 Difference in annual recharge for the four scenarios generated for the Nuenna (a,b,c,d), Mattock (e,f,g,h) and Dripsey (i,j,k,l) considering: Low recharge cap values (-50 mm/y) Medium-Low cap values (-25 mm/y), Medium-High cap values (+25 mm/y) and High cap values (+50 mm/y)

Any variation of the recharge cap generates a homogeneous response in recharge for the permeable areas (Figure 4.10). Nevertheless, the low permeability areas present a smaller range of change. For instance, in the Dripsey catchment, a decrease of 50 mm/y in the recharge cap is translated into an even reduction of 50 mm/y recharge through the entire

area with the exception of the headwaters, which are covered with peat, and around the river channel, covered by alluvium. Hence, even though the recharge caps have a larger control on groundwater recharge, low permeability subsoil areas are less sensitive and smooth the effect of the variations applied.

4.3.2.3 Rainfall intensity

The modification of the rainfall series has been achieved by preserving the annual totals and altering the percentage occurrence of rain days. The addition and removal of rain days was done by a stochastic forcing, a process which is randomly based on the likelihood of events occurring in each month. In this way, wetter months have a greater chance of having a rainy day added and vice versa. The increment of intensity is performed by removing wet days while fixing the annual average, so the intensity of the remaining days needs to be higher in order to preserve the total. Four new precipitation scenarios were generated: two in which rainfall intensity was incremented by 10% and 20%, and two more in which the intensity was reduced by the same percentages. The results suggest that an increase of rainfall intensity would lead to higher annual groundwater recharge (Figure 4.11). Nevertheless, the effect of the changes of intensity are only apparent in those areas that are not affected by recharge caps i.e. areas underlain by aquifers with good storage and throughput capacity, such as the regionally important limestone aquifer that occupies the centre of the Nuenna catchment. In contrast, the areas affected by recharge caps - namely, the margins of the Nuenna catchment and the entirety of the Dripsey and Mattock catchments - show very little variation to these changes (± 10 mm/y) in rainfall intensity.

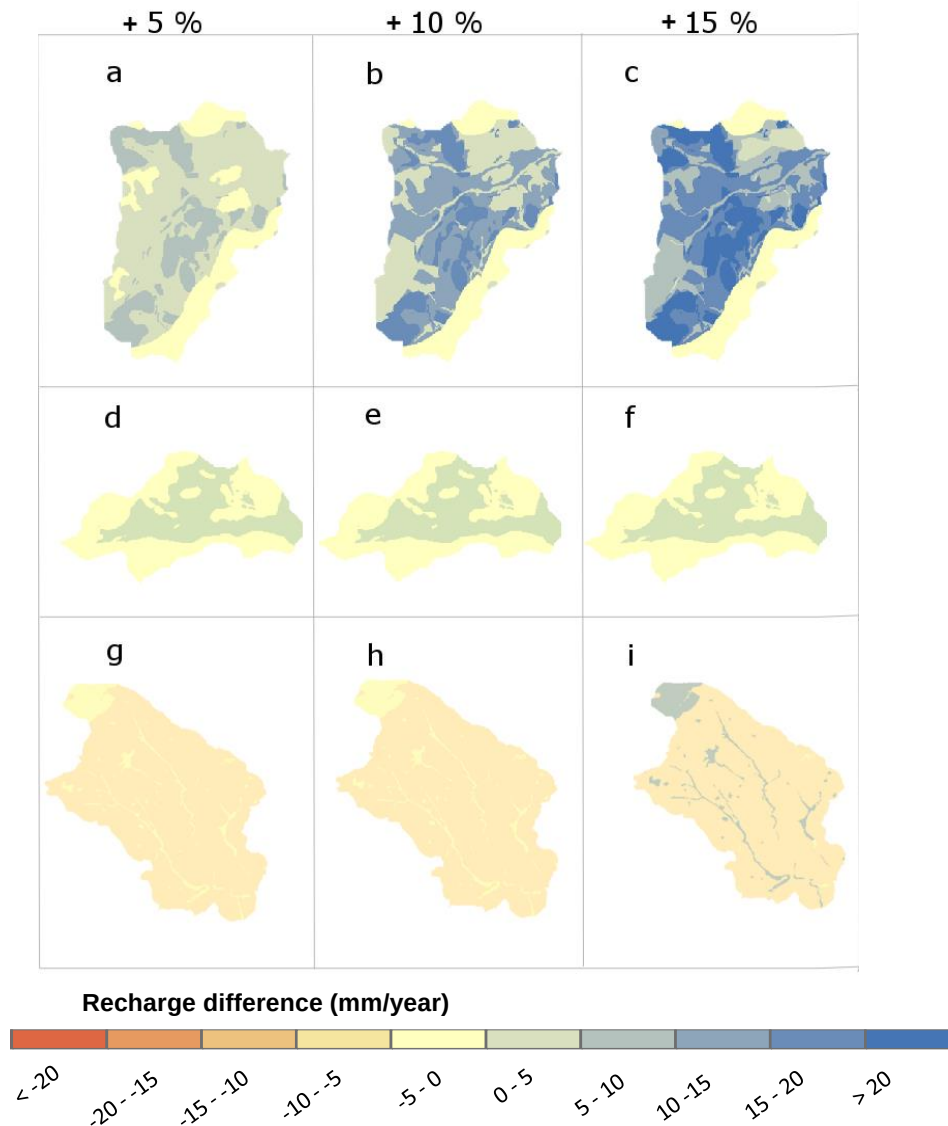


Figure 4.11: Recharge scenarios for the Nuenna catchment (a,b,c,d), Mattock (e,f,g,h) and Dripsey (i,j,k,l) under changing rainfall intensities

4.3.2.4 Rainfall seasonality

The alterations to the rainfall seasonality were performed in a similar manner to those presented above for rainfall intensity: by fixing the annual averages, then increasing the number of wet-days for the winter months (December, January and February), and reducing the number in the summer months (June, July and August), by a set percentage in each case. The results obtained suggest that, similar to the rainfall intensity variations, an amplification of rainfall seasonality would lead to an increase in annual recharge due to a significant rise of recharge during winter in the areas not affected by recharge caps (Figure 4.12). However,

as expected, the impacts on the catchments fully underlain by poorly productive aquifers are minimal.

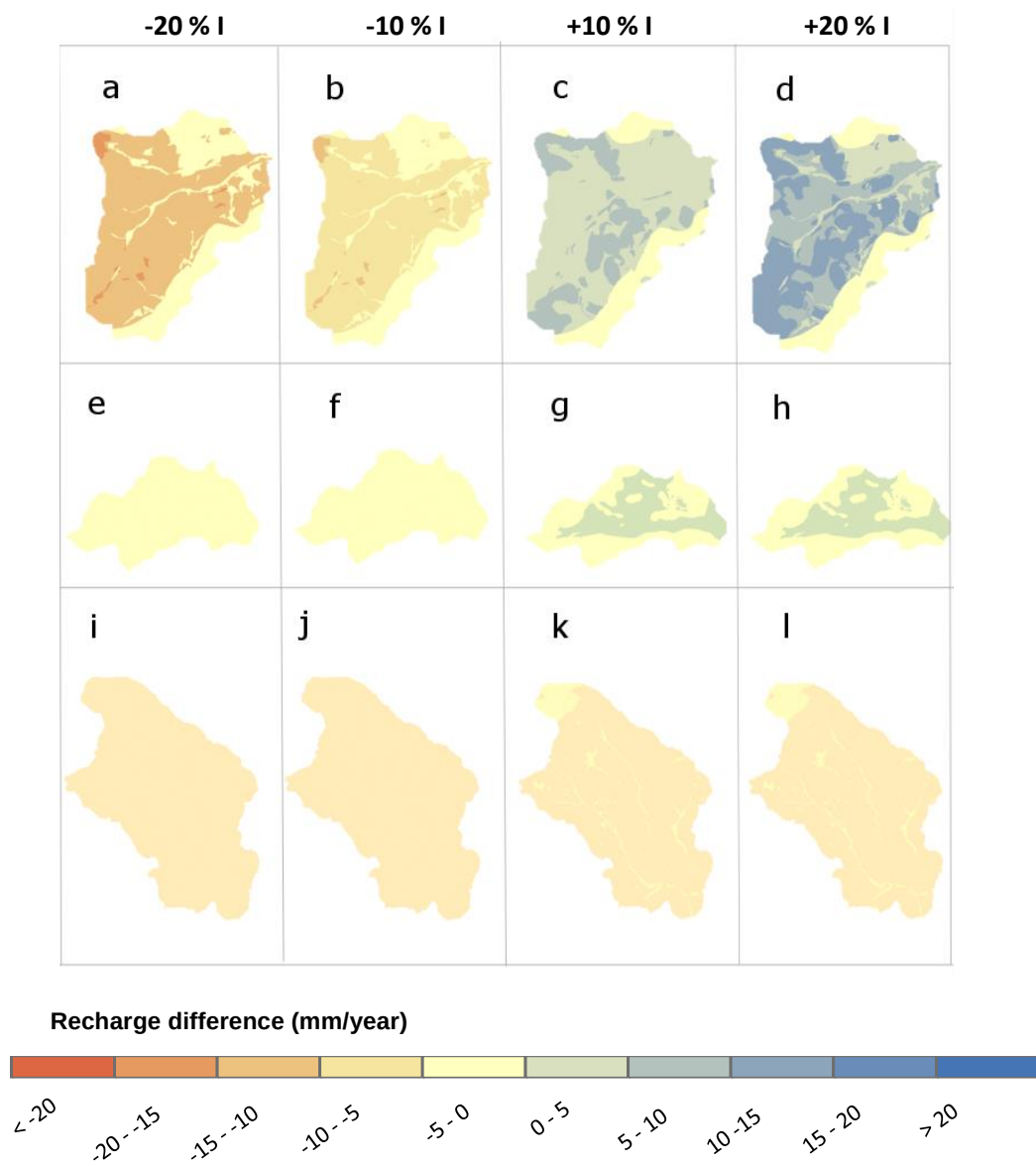


Figure 4.12: Recharge scenarios for the Nuenna catchment (a,b,c,), Mattock (d,e,f) and Dripsey (g,h,i) under amplified rainfall seasonality scenarios

4.4 Conclusions and Discussion

The sensitivity analysis has investigated the effect of changes in the hydrogeological and hydrometeorological variables that control groundwater recharge within the Irish context. The hydrogeological variables represent common hydrogeological settings within Ireland, whilst the hydroclimatic variables explored possible changes in climate as anticipated by climate projections.

The results obtained for the general analysis conducted for Co. Kildare show a clear direct relationship with rainfall rates, and an indirect relationship with AE rates, as expected. The results also suggest a linear relationship with both recharge coefficients and recharge caps. However, the effects of the variation in rainfall, AE and recharge coefficients are subject to the aquifer's storage capacity; if the underlying aquifer is affected by a recharge cap, then the variation of any of the other variables considered is buffered. Similar results were obtained at a catchment scale.

Furthermore, the results suggest that any increases in rainfall intensity or seasonality would lead to an increase of annual recharge due to a reduction in actual evapotranspiration. The effect of changing rainfall intensity or seasonality is most marked in areas with high recharge coefficients and which are not affected by recharge caps. Consequently, the extent of the effect of changes in rainfall intensity and seasonality is strongly influenced by the local hydrogeological settings. This would lead to an unequal impact around the country, owing to the heterogeneous nature of the hydrogeology. Overall, these results are consistent with those obtained by Fitzsimons and Misstear (2006), which suggested that the till thickness, and especially its permeability, have a greater effect on the recharge estimations than the soil moisture budgeting parameters (i.e: effective rainfall), and highlight the danger of limiting recharge estimations to meteorological and soil properties, without taking into consideration geological and hydrogeological features in humid climates.

5. Soil Moisture Budgeting and the Unsaturated Zone

5.1 Introduction

The results of the sensitivity analysis presented in the previous chapter have demonstrated that, in the Irish context, groundwater recharge is primarily controlled by the aquifer's storage capacity, followed by the permeability of the overlying soils and subsoils which are represented by recharge coefficients. These recharge coefficients represent the percentage of effective rainfall becoming actual groundwater recharge (Hunter Williams et al. 2013) and, therefore, are an indirect representation of the infiltration processes through the unsaturated zone to the water table.

As presented in Chapter 2, a significant part of Ireland is covered by glacial deposits, which are characteristic by having a low permeability. In fact, the sensitivity analysis carried out by Fitzsimons and Misstear (2006), concluded that the permeability of the tills has the largest control on the volume of water recharging the aquifer, followed by the till's thickness. Therefore, given the observed importance of this hydrogeological feature, these processes are examined further in this chapter - from the soil moisture budget parameters to the infiltration capacity of the subsoils.

The potential evapotranspiration (PE) is a key flux for hydrological processes and an important input to hydrological model applications (Andréassian et al. 2004). There are over fifty methods to estimate PE (Lu et al. 2005), making the choice of method complicated. Hence, this choice is often subject to data availability and the criteria of the researcher. It does not come as a surprise then, that there is a significant number of comparative studies as well as evaluations of the methods for different climates (e.g. Chen et al. 2005; Lu et al. 2005; Oudin et al. 2005; Xiaoying and Erda 2005; Berti et al. 2014; McMahon et al. 2016; Lang et al. 2017). For this reason, the Food and Agriculture Organisation (FAO) recommended the use of the modified Penman-Monteith equation when there is sufficient data as it is considered the best calculation method for most environments (Allen et al. 1998a). However, the data required for the application of the Penman-Monteith equation is often unavailable, in which case, the FAO recommends using the Hargreaves equation.

The unsaturated zone plays a critical role in the hydrological cycle as several processes such as infiltration, evapotranspiration and soil moisture storage occur within the vadose zone. In the last few decades, there has been considerable progress in the understanding and modelling of the different processes taking place in this zone. Quantifying infiltration has been the focus for much of the research from the agricultural and water resources perspective because of its fundamental role in groundwater hydrology and agricultural applications (Milla and Kish 2006). There are a considerable number of mathematical models available to simulate infiltration; however all those models based on semi-empirical or empirical relationships cannot provide a detailed explanation of the processes and their physical meaning is not robust (Ma et al. 2010). For this reason, physically-based models such as the Richards equation (Richards 1931) and the Green-Ampt model (Green and Ampt 1911) are more commonly used (Simunek et al. 2009). The Hydrus software package (Simunek et al. 2009) is a specialised model to simulate water flow and transport through the unsaturated zone, which includes several of these models, and is commonly used in hydrology to model infiltration and groundwater recharge (e.g. Leterme et al. 2012; Dickinson et al. 2014; Pfleetschinger et al. 2014; Turkeltaub et al. 2015; Yu et al. 2015).

As extreme events are anticipated under the ongoing climate change, it is particularly important to understand the role of the unsaturated zone, and to assess the infiltration capacity of the soils. Therefore, in this chapter, two different aspects of the infiltration processes through the unsaturated zone are addressed: the soil moisture budget and the infiltration capacity.

In the first part of this chapter, the impact of the choice of the PE estimation method is evaluated by comparing three common approaches (i.e. Penman-Monteith, Hargreaves and Blaney-Criddle). Furthermore, as this project is framed as a climate change impact assessment, this evaluation will also be used to choose the most appropriate method to calculate PE under future climate conditions. Next, the Penman-Monteith-FAO soil moisture budget (Allen et al. 1998b) is applied to estimate the actual evapotranspiration (AE) and infiltration within the three study catchments considered in the sensitivity analysis (Chapter 4) namely, Nuenna, Mattock and Dripsey (see Section 3.2.1). Finally, the modified rainfall time series used in the sensitivity analysis are also used here to assess the sensitivity of the soil moisture budget parameters to rainfall intensity and seasonality. The first part of this chapter constitutes, then, a continuation of the sensitivity analysis, where the effect of the soil moisture budget parameters and PE methods are analysed. Hence, it should be noted

that the results obtained - similarly to those of the sensitivity analysis - provide an assessment of the average annual groundwater recharge at the three study catchments.

In the second part of the chapter, the Hydrus-1D software has been implemented in two supplementary study sites, namely Crecora and Kilmallock (see Section 3.3) to evaluate the infiltration capacity of these sites. Given that the objective of this modelling exercise is to determine rainfall intensity thresholds from runoff generated by excess of saturation, the working time resolution ranges from hourly to daily in order to capture the effect of intense rainfall events.

5.2 Methods

In this section a detailed description of the methodology followed in this chapter is presented. It should be borne in mind that different study areas and different data sets are used. In the first part, the catchments and datasets are the same as those used in Chapter 4 and introduced in Chapter 3 (see Figure 3.1). In contrast, the second part of the analysis is performed on two additional study sites as the data required was not available for the main groundwater recharge study catchments (see Figure 3.12).

5.2.2 Potential Evapotranspiration and Soil Moisture Budget

Evaporation is the process whereby liquid water is converted into vapour and is consequently removed from an evaporating surface. In nature, water can evaporate from a large variety of surfaces; surface water bodies (e.g. seas, rivers, lakes), soil surface and wet vegetation. Similarly, the transpiration processes also consist of the vaporisation of liquid water and its removal to the atmosphere. However, in this case, the water vaporised is not on surfaces, but rather contained in the vegetation tissues. Given that the two processes occur simultaneously, it is complicated to differentiate them and so they are normally estimated together as evapotranspiration (ET), which accounts for the total water vaporisation within an area. Some of the factors that govern evapotranspiration are solar radiation, temperature, relative humidity, soil moisture, wind speed and vegetation presence and density. As the climate conditions are an important limiting factor, there are two ways of considering ET: (1) potential evapotranspiration (PE), i.e. the ET that would occur under given climatic conditions if there was unlimited soil moisture, and (2) actual evapotranspiration (AE), which refers to the ET that actually occurs under given climatic and soil moisture conditions.

ET can be directly estimated through pans, lysimeters and atmometers. Nevertheless, these methods provide local point information that needs to be extrapolated to wider areas and are often not available in any case. Therefore, it is a more common approach to calculate PE from the range of existing equations which consist of theoretical, semiempirical and empirical models. Then, once PE has been estimated, AE can be calculated using soil moisture budget techniques such as the proposed by the FAO or Teagasc (Allen et al. 1998b; Schulte et al. 2005).

5.2.3 PE estimation techniques

The instrumentation required to estimate ET directly is not generally available. This is the case in the Republic of Ireland, where there are no public records of measured ET, and the available data from Met Eireann consist of calculated PE through the modified Penman-Monteith formula. These PE estimations are then transformed into AE based on the hybrid soil moisture budget model developed by Teagasc and used by Met Eireann (Schulte et al. 2005).

As mentioned above, one of the aims of this section is to evaluate several PE estimation techniques to determine which one could provide less uncertain PE values under future climate scenarios. Hence, even though the use of the modified Penman-Monteith equation is recommended by the FAO, the large data requirements for the application of this equation must be considered and consequently, the unavailability of some of these variables for climate projections, as well as the uncertainty associated with those available variables. Therefore, unlike the Met Eireann PE estimates, the modified Penman-Monteith applied below assumes that net radiation data is not available as it would be the case in climate projections. Hence, the PE estimates of the two versions are compared with each other as well as, the PE values obtained by simpler methods such as Hargreaves-Samani and Blaney-Criddle.

5.2.3.1 *Modified Penman-Monteith*

The modified Penman-Monteith or FAO-56 Penman-Monteith equation (Allen et al. 1998a) is considered to be the most accurate method for calculating the potential

evapotranspiration under most climatic conditions (Chen et al. 2005), and can be calculated following the equation below:

$$PE = \frac{0.408\Delta (R_n - G) + \gamma \frac{900}{T + 273} U_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (5.1)$$

where PE is the reference crop evapotranspiration expressed in mm/day, R_n is the net radiation at the crop surface ($\text{MJ/m}^2 \text{ day}$), G is the soil heat flux density ($\text{MJ/m}^2 \text{ day}$), T is the mean daily air temperature at 2 m height ($^{\circ}\text{C}$), U_2 is the wind speed at 2 m height (m/s), e_s is the saturation vapour pressure (kPa), e_a is the actual vapour pressure (kPa). Hence the term $e_s - e_a$ represents the saturation vapour pressure deficit (kPa), Δ is the slope of the vapour pressure curve ($\text{kPa}/^{\circ}\text{C}$), and γ is the psychrometric constant ($\text{kPa}/^{\circ}\text{C}$).

As this equation is intended to be applied to estimate PE under future climate scenarios, net radiation (R_n) needs to be approximated through the Angstrom formula which relates solar radiation to extraterrestrial radiation and relative sunshine:

$$R_s = \left(a_s + b_s \frac{n}{N} \right) R_a \quad (5.2)$$

where: R_s is the solar radiation, a_s and b_s are regression constants, expressing the fraction of extraterrestrial radiation reaching the earth which are estimated by Met Eireann as 0.23 and 0.57, respectively. n/N represents the relative sunshine duration (actual vs maximum) and R_a is the extraterrestrial radiation which can be calculated through the equation:

$$R_a = \frac{24(60)}{\pi} G_{sc} d_r [\omega_s \sin(\varphi) \sin(\delta) + \cos(\varphi) \cos(\delta) \sin(\omega_s)] \quad (5.3)$$

where φ is the latitude expressed in radians:

$$\varphi = \frac{\text{lat} \pi}{180} \quad (5.4)$$

ω_s is the sunset hour angle:

$$\omega_s = \arccos[-\tan(\varphi) \tan(\delta)] \quad (5.6)$$

δ is the solar declination:

$$\delta = 0.409 \sin\left(\frac{2\pi}{365} J - 1.39\right) \quad (5.7)$$

where J is the Julian day of the year and d_r is the inverse relative distance earth-sun:

$$d_r = 1 + 0.033 \cos\left(\frac{2\pi}{365} J\right) \quad (5.8)$$

and G_{sc} is the solar constant:

$$G_{sc} = 0.0820 \text{ MJ}/\text{m}^2 \text{ min} \quad (5.9)$$

Then, the net shortwave radiation can be estimated:

$$R_{ns} = (1 - a)R_s \quad (5.10)$$

where a is the albedo reflection coefficient, which is 0.23 for the reference crop. Similarly, the net longwave can also be determined through the expression below:

$$R_{nl} = \sigma 2 \left[\frac{T_{maxk} + T_{minK}}{2} \right] (0.34 - 0.14\sqrt{e_a}) \left(1.35 \frac{R_s}{R_{so}} - 0.35 \right) \quad (5.11)$$

where the T_{maxk} and T_{minK} represent the maximum and minimum temperatures represented in Kelvin, and R_{so} is the clear-sky radiation, which can be calculated from the regression coefficients presented in Equation 5.2 and the extraterrestrial radiation (R_a):

$$R_{so} = (a_s + b_s)R_a \quad (5.13)$$

Finally, the net radiation can be estimated from the difference between short and longwave radiation:

$$R_n = R_{ns} - R_{nl} \quad (5.13)$$

Similarly, the saturation vapour pressure deficit term also needs to be estimated through the equations:

$$e_s = 0.6108 \exp \left[\frac{17.27T}{T + 273.3} \right] \quad (5.14)$$

$$e_a = 0.6108 \exp \left[\frac{17.27 T_{dew}}{T_{dew} + 273.3} \right] \quad (5.15)$$

These two operations are performed twice; with maximum and minimum temperature (Equation 5.14) and with maximum and minimum dew temperature (Equation 5.15) that are

then averaged to estimate the saturation vapour pressure(e_s) and the actual vapour pressure (e_a) respectively.

5.2.3.2 *Hargreaves*

The Hargreaves and Samani equation (Hargreaves and Samani 1985) is a semiempirical method to calculate potential evapotranspiration from maximum and minimum temperatures, that can be applied at different temporal resolutions:

$$PE = 0.0023 R_a (T + 17.8) \sqrt{T_{max} - T_{min}} \quad (5.16)$$

where the notation is the same than in the description of the Penman-Monteith equation, and R_a can be estimated from Equation 5.3.

5.2.3.3 *Blaney and Criddle*

The Blaney and Criddle (1950) equation is another theoretical method to approximate PE when the data to apply Penman-Monteith is not available. This is a simplistic approach based on mean temperature rather than solar radiation. It is for this reason, that this equation is likely to be less accurate than other methods that do incorporate a radiation term. Furthermore, the FAO points out that this method accuracy is rough and, therefore, the results should be interpreted as initial estimations or order of magnitude. It is also highlighted that this method can overestimate PE up to a 40% in humid and clouded areas such as Ireland (Allen 1986). According to this method PE can be estimated as:

$$PE = p(0.457 T_{mean} + 0.128) \quad (5.17)$$

Where p is the mean daily percentage of annual daytime hours.

5.2.3.4 *Soil Moisture Budget*

The calculation of the Actual Evapotranspiration (AE) from PE values was achieved through the application of the FAO Penman-Monteith soil moisture budgeting approach (Allen et al. 1998a). In this case, as the calculations are started in January it is reasonable to assume that there is no soil moisture deficit at the start of these computations and, therefore, that in this case the AE is equal to the PE. As a first step, the total available water (TAW) and readily

available water (RAW) are estimated for each catchment from previous studies (O'Brien 2013) and the FAO recommendations (Allen et al. 1998b).

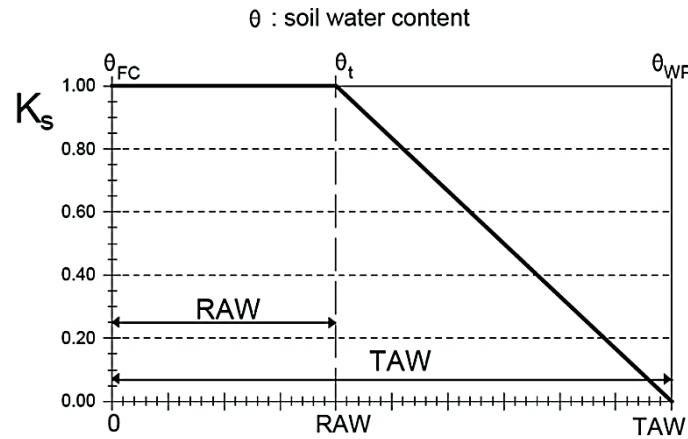


Figure 5.1: Dependency of the water stress coefficient (K_s) depending on the soil moisture content. θ_{FC} and θ_{WP} represent the soil water content for the field capacity and wilting point respectively. θ_t represents the critical soil water corresponding to the limit of the RAW from which water stress occurs. Source: Allen, 1998.

The TAW represents the volume of water contained on the soil that the vegetation can use without permanent wilting occurring. Its maximum volume is defined by the field capacity, whereas its minimum is fixed by the wilting point. However, vegetation suffers hydric stress before going into permanent wilting. Hence, the RAW defines the portion of TAW in which plants can suction water from the soil without suffering hydric stress. Once the threshold value defined by the RAW is surpassed, AE cannot longer be equal to PE, and it decreases linearly until the wilting point, where no AE is possible (Figure 5.1). The rate at which AE decreases can be estimated through the water stress coefficient:

$$K_s = \frac{TAW - D_r}{TAW - RAW} \quad (5.18)$$

where K_s represents the water stress coefficient, and D_r is the soil moisture deficit. From this stress coefficient the new AE for a given time step can be calculated from:

$$AE = PE \cdot K_s \quad (5.19)$$

Nevertheless, this approach considers the AE for a reference crop, which corresponds to 12 cm high grassland. Therefore, a crop coefficient must be applied when other crops are within the area studied: in this case, the three study catchments used in the sensitivity analysis: Mattock, Dripsey and Nuenna. Despite being covered mostly by pastures, about 20% of each catchment surface has another land use or crop (see Section 3.2). Hence, the GIS analysis

performed for the catchment descriptions in Section 3.2 has also been used to perform a distributed soil moisture budget according to the different land-uses within each catchment. Then, a general AE and infiltration value is calculated by a weighted average based on the percentage that each land-use represents on the catchment.

This approach has been implemented in this chapter to evaluate the annual AE and infiltration cycles as well as the AE/PE ratio for the three catchments (i.e. Mattock, Dripsey and Nuenna). Furthermore, the modified rainfall time series used in Chapter 4 for the sensitivity analysis have also been used here to test the sensitivity of the AE and infiltration to the simulated changes in rainfall (see Section 4.2).

5.2.4 Infiltration Capacity

The sensitivity analysis performed in Chapter 4, has demonstrated the importance of the unsaturated zone (recharge coefficients) on groundwater recharge processes. To further explore the effect of the soil and subsoil permeability, here the infiltration capacity of two study sites is tested through the implementation of Hydrus 1-D (Simunek et al. 2009). As the data required for this kind of study was not available for the selected study catchments, two additional sites were used for this purpose: the Creccora and Kilmallock sites (see Section 3.3). Their relevant hydrogeological characteristics are summarized in Table 5.2.

Table 5.2: Hydrogeological settings of the study sites

	Creccora	Kilmallock
Bedrock	Wallsortian Limestones	Dinatian Limestones
Aquifer category	Regionally important (Rkd)	Locally important (LI)
Vulnerability	High	Moderate
Soil permeability	Moderate	Moderate
Soil drainage	Dry	Dry
Effective Rainfall	565 mm/y	560 mm/y
Recharge coefficient	60 %	60 %
Recharge cap	No	Yes (200)
Recharge	340 mm/y	200 mm/y

The modelling of water infiltration through the unsaturated zone has been carried out with the Hydrus 1-D software, which is a package for simulating the water infiltration (or vertical heat propagation) and solute transport for variable-saturated water flow. The simulation of

these flows is achieved by solving numerically the Richards equation given specific initial and boundary conditions. Here, infiltration is simulated within Hydrus using a modified form of the Richards equation, which assumes that the effect of the air phase is negligible as well as the water flow due to thermal gradients, and can be expressed as:

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x} \left[K \left(+ \frac{\partial h}{\partial x} \cos \alpha \right) \right] - S \quad (5.20)$$

where θ is the volumetric water content, t is time, x is the spatial coordinate that indicates the direction of the flow (negative for infiltration). h is the water pressure head, α is the angle between the flow direction and the vertical axis (i.e. $\alpha = 0^\circ$ in this case). S is a sink term representing the roots water uptake, and K is the unsaturated hydraulic conductivity given by:

$$K(h, x) = K_s(x)K_r(h, x) \quad (5.21)$$

where K_r is the relative hydraulic conductivity and K_s the saturated hydraulic conductivity.

The data provided (Knappe, 2019) included the time-series of the volumetric water content at different depths, as well as the soil profile and textural classification according to the UK SSEW (RDS,2006) and some of the required input soil properties such as the bulk density or saturated conductivity (see Section 3.3). The availability of these data allowed first the use of an inverse modelling approach to estimate more accurately some of the soil parameters within the study sites. Then, once the soil parameters are established, they are used in a conventional direct approach to assess the infiltration capacity of the soils. To do so, the rainfall intensities are progressively increased until runoff is generated.

The software includes up to six hydraulic models from which the hydraulic properties of the soils are simulated. Here, a single porosity (van Genuchten 1980) hydraulic model has been applied in both study sites; however, no hysteresis has been considered. Although the software package has the potential to simulate infiltration using a more complicated dual-permeability model to represent both, matrix and macropores, it has not been used in this case as the aim of the modelling is to gain more general information about the recharge processes rather than detailed site understanding.

The simulations have been run for daily timesteps, and daily variations in evapotranspiration have been considered (Hydrus generated). The differences in the modelling settings between

the two sites are: (1) the length of the simulations, which is linked to the available data and (2) the specific boundary conditions for each study case (Table 5.3). Finally, the initial conditions have been set to the value of the corresponding first day of observations.

Table 5.3: Simulations settings

	Creccora	Kilmallock
Simulation Duration (days)	677	710
Soil Thickness (m)	3	1.6
Upper boundary condition	Atmospheric with Surface Runoff	Atmospheric with Surface Runoff
Lower boundary condition	Free drainage	Constant water content (simulating water table at 1.6 m)

5.3 Results

5.3.2 PE estimation techniques

The equations presented in Section 5.2.3 have been applied to obtain daily PE estimations for the three catchments that have been then averaged to get the annual variation. Figure 5.2 displays the annual cycle of each one of these PE estimations in comparison to the PE available from Met Eireann. At first sight, it can be appreciated that the Blaney-Criddle method overestimates PE through the year for the three catchments. The Penman-Monteith estimations, in contrast, present an irregular performance; it represents a practically identical annual cycle for the Nuenna catchment (Figure 5.2a) - with just a slight underestimation for the warmest months - but appears to overestimate the PE from September to March in the Mattock (Figure 5.2b) and the Dripsey (Figure 5.2c) in comparison to the Met Eireann data. Moreover, it continues to underestimate the PE for the summer months. The PE values obtained through the application of the Hargreaves equation are those closer to the Met Eireann estimations in the three study areas. The results achieved by this method, represent a good fit to the Met Eireann values at the Nuenna, however, it

appears to underestimate the PE for the summer months, despite the average daily difference being inferior at 0.5 mm in all the cases.

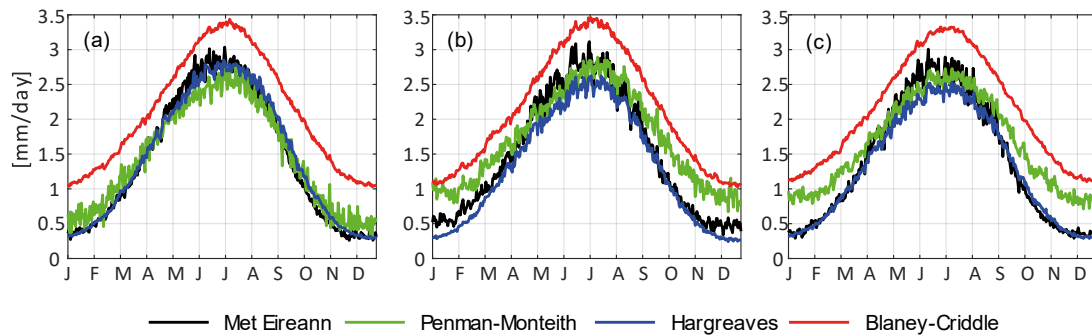


Figure 5.2: PE annual cycle calculated from average daily PE calculated by Met Eireann (black), and the application of the Penman-Monteith (green), Hargreaves (blue) and Blaney-Criddle (red) equations for (a) the Nuenna, (b) the Mattock and (c) the Dripsey catchments.

Given the results presented above, and the simplicity of the method, it is logical to conclude that the Hargreaves technique should be used under future climate scenarios to estimate PE. Furthermore, this approach has low data requirements being a mainly temperature-based method, which is one of the most robust variables within the climate projections (see Section 2.4.1). Hence, by avoiding using more uncertain variables such as wind-speed it would help to reduce the accumulated uncertainty under future climate scenarios. Nevertheless, it must be borne in mind that it is assumed that the equations to estimate the solar radiation remain valid.

5.3.3 Budgeting techniques: Soil moisture budget and Water Balance

The soil moisture budgeting approach presented above (Section 5.2.3) has been used in the three catchments (Nuenna, Dripsey, Mattock) to estimate the annual cycle at a daily resolution for the four main variables involved in the soil moisture budget, namely: rainfall, infiltration, PE and AE (Figure 5.3).

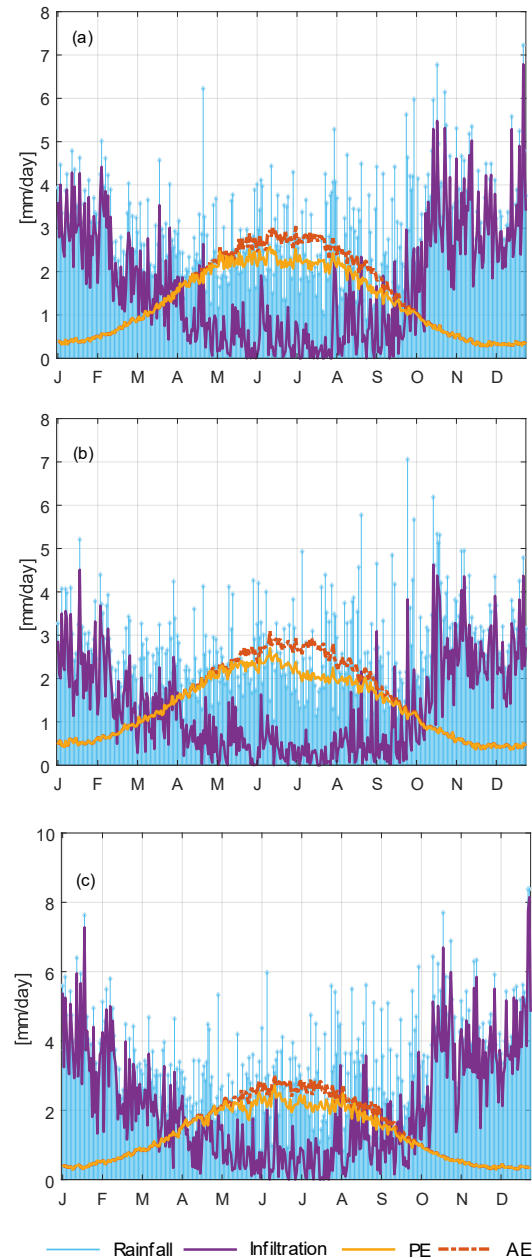


Figure 5.3: Average annual soil moisture budget for (a) the Nuenna, (b) the Mattock and (c) the Dripsey catchments. Daily values of incoming rainfall (light blue), PE (orange), AE (dark yellow), and infiltration (purple) are represented.

The results obtained show that the three catchments present a very similar annual cycle, with water stress occurring from May to October as the difference between PE and AE suggests. As expected, infiltration presents an inverted annual cycle with respect to PE, so it achieves its maximum values in winter, and its minimums in the middle part of the year when there is a soil moisture deficit, and most of the soil water content is evaporated. This would indicate that, as expected, most of the annual groundwater recharge takes place during winter.

The same soil moisture budget has then been forced with the synthetic rainfall series generated in Chapter 4, which simulate increased and decreased rainfall intensity but also enhanced seasonality. In this way, the sensitivity of the AE and Infiltration to changes in rainfall intensity and seasonality has been tested, and the results are presented in Figure 5.4. The modification of rainfall intensity has little effect on the infiltration annual cycle as it presents just a slight increase in the wet months for increased intensities, and small reduction in the warm months from the reduced intensities. The AE cycle presents a clearer sensitivity, even though it is also focused on the summer months. In this case, an increased (decreased) rainfall intensity would lead to lower (higher) AE.

Furthermore, the AE annual cycle obtained from the enhanced seasonality rainfall series presents a similar behaviour than observed with the rainfall intensities. In all the scenarios considered, an enhanced seasonality leads to an AE reduction from May to September but has no effect on the rest of the months, as there is no water deficit. Similarly, the Infiltration cycle shows also a reduction of infiltration during the same months, but a clear increase in the winter months. Therefore, an enhanced rainfall seasonality with higher rainfall in winter and lower in summer would cause higher infiltration in the winter months and lower in the summer months, as it would be expected. These results are consistent with the annual averages, which indicate an increase (decrease) of Infiltration (AE) with higher (reduced) rainfall intensity, as well as, larger (lower) infiltration (AE) with enhanced rainfall seasonality as it is shown in Table 5.4.

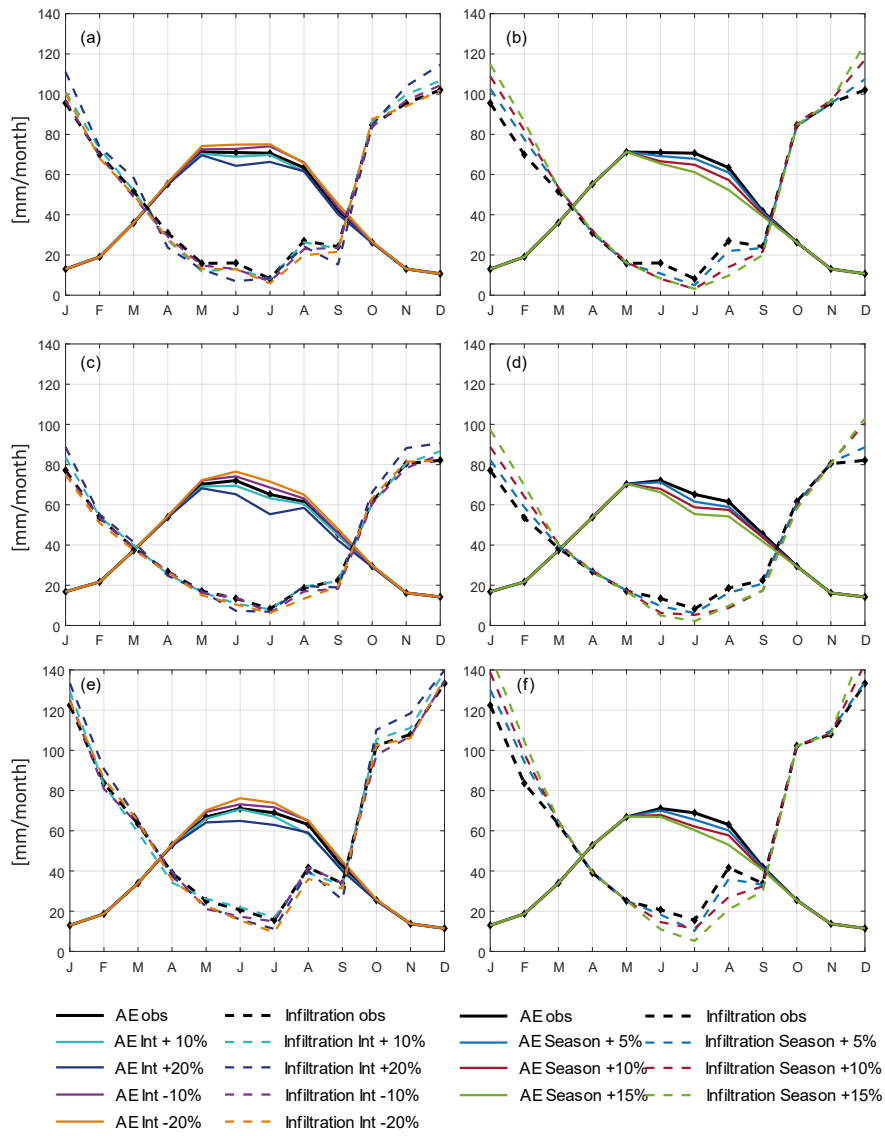


Figure 5.4: Sensitivity of the AE and Infiltration to rainfall intensity (left column) and seasonality (right column), for the Nuenna (first row), Mattock (middle row) and Dripsey (last row) catchments.

Table 5.4: Actual evaporation, AE/PE ratio and Infiltration annual averages estimated from the observations, and the modified rainfall series.

NUENNA			
	AE (mm/y)	AE/PE (mm/y)	Infiltration (mm/y)
Observations	475	0.89	600
Intensity (+ 10%)	468	0.88	607
Intensity (+ 20%)	460	0.86	616
Intensity (- 10%)	486	0.91	589
Intensity (- 20%)	493	0.93	583
Seasonality (+5%)	468	0.88	607
Seasonality (+10%)	458	0.86	617
Seasonality (+15%)	447	0.84	628
MATTOCK			
	AE (mm/y)	AE/PE (mm/y)	Infiltration (mm/y)
Observations	488	0.89	483
Intensity (+ 10%)	480	0.88	490
Intensity (+ 20%)	463	0.86	507
Intensity (- 10%)	497	0.92	473
Intensity (- 20%)	507	0.94	465
Seasonality (+5%)	480	0.88	491
Seasonality (+10%)	472	0.87	499
Seasonality (+15%)	462	0.85	509
DRIPSEY			
	AE (mm/y)	AE/PE (mm/y)	Infiltration (mm/y)
Observations	465	0.9	762
Intensity (+ 10%)	456	0.89	771
Intensity (+ 20%)	445	0.86	783
Intensity (- 10%)	477	0.93	750
Intensity (- 20%)	484	0.94	744
Seasonality (+5%)	458	0.89	770
Seasonality (+10%)	449	0.87	778
Seasonality (+15%)	441	0.86	786

5.3.4 Infiltration Capacity

In a first modelling step, the soil water content and soil water properties have been used in an inverse modelling exercise to determine the Θ_R and Θ_S parameters, whereas the rest of the parameters of the soils summarised in Table 5.5 have been obtained from Knappe (2019). As can be observed, most of the parameters are close, as would be expected from the textural soil classification.

Table 5.5: Soil Parameters estimated from the Inverse modelling approach carried out for the two study sites. Θ_R and Θ_S represent the residual and saturated soil water content respectively. α and N are parameters of the soil water retention curve, K_s stands for saturated hydraulic conductivity, and L is the tortuosity parameter in the conductivity function.

Crecora						
Soil texture	Θ_R	Θ_S	α [mm ⁻¹]	N	K_s [mm/day]	L [-]
Loam	$6.3 \cdot 10^{-2}$	0.384	$0.1 \cdot 10^{-2}$	1.51	$1.3 \cdot 10^2$	1.005
Kilmallock						
Sandy Loam	$3.9 \cdot 10^{-2}$	0.387	$0.2 \cdot 10^{-2}$	1.45	310	1

To investigate the infiltration capacity of these soils, the soil parameters presented in Table 5.4 have been used to model the infiltration during 14 days in winter, with real PE data and modified rainfall to simulate one single day of rainfall. The rainfall was progressively increased to detect threshold values from which runoff is generated. Runoff is first detected from 95mm/d and 120mm/d for the Crecora and Kilmallock sites, respectively.

Nevertheless, numerical solutions of highly nonlinear Richards equation require relatively fine spatial and temporal discretization (Šimůnek and Weihermüller 2018). The resolution of the discretization depends on the rainfall and evaporation rates, but also on the soil texture; for instance, coarse-textured soils with relatively high n and α values (van Genuchten 1980) require a finer spatial discretization than fine soils, as their hydraulic functions are more nonlinear and, consequently, the numerical solution is less stable (Radcliffe and Šimůnek 2010). Furthermore, an appropriate temporal resolution of the meteorological inputs (i.e. precipitation and evapotranspiration) is crucial for capturing the generation of runoff by excess of saturation (Hortonian flow), as using a coarse temporal resolution could lead to the

overestimation of infiltration and underestimation of runoff (Šimůnek and Weihermüller 2018).

Considering the results presented above, it is likely that this is the case in the previous approach to evaluating the infiltration capacity of the soils considered. Therefore, the modelling exercise is repeated but, in this case, one single day is simulated, and the temporal discretization is at hourly time steps rather than daily. Then, rainfall is progressively increased in one particular time step until surface runoff is detected. With this finer temporal resolution, new threshold values are obtained; whereas a minimum of 6.5 mm/h of rainfall is required to generate 5 mm of runoff at the Crecora site, and 12 mm/h generate a similar amount for the Kilmallock site. If these rainfall rates were to be constant through an entire day, it would result in higher values than those estimated at daily resolution. Nevertheless, despite being high rainfall rates, short and intense rainfall events of up to 12 mm/h are more plausible than daily rainfall accumulations of over 100 mm/day.

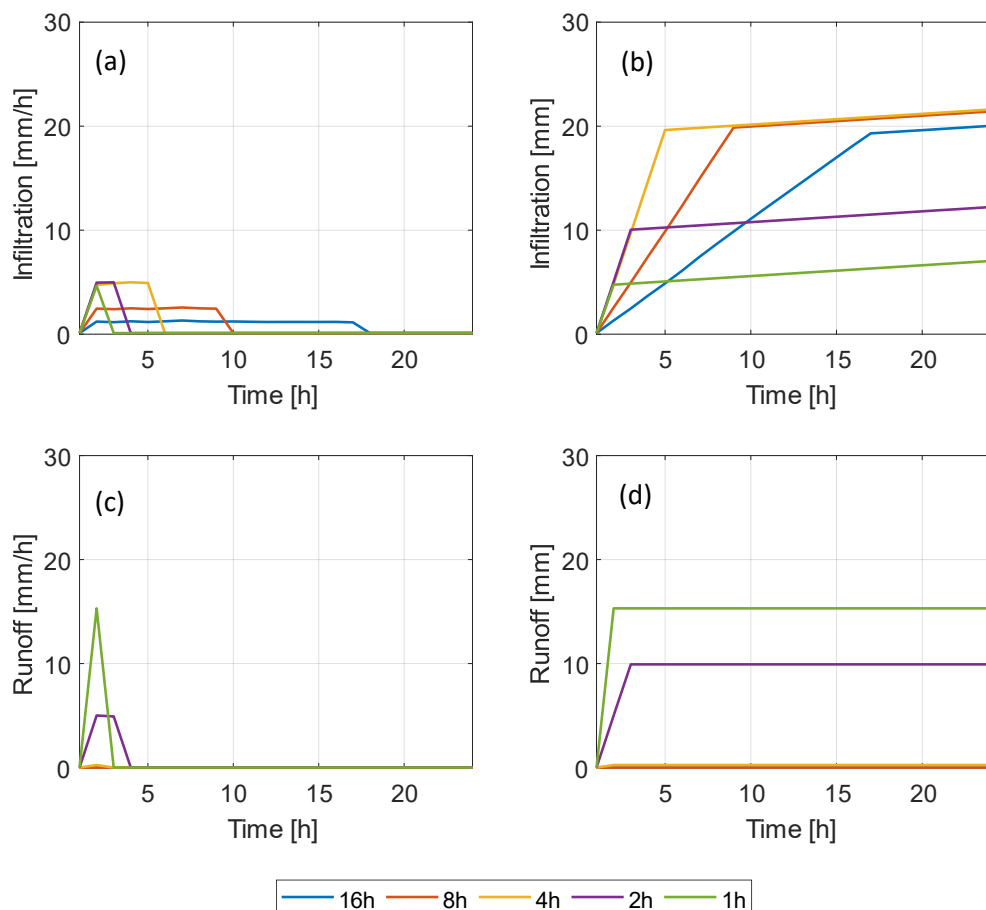


Figure 5.5: Infiltration rate (a), and cumulative infiltration (b) generated from 100mm rainfall distributed in 1h (green), 2h (purple), 4h (yellow), 8h (orange) and 16h (blue) events and the corresponding runoff generated (c), and total runoff (d) at the Crecora site.

In order to compare the two results obtained, another infiltration capacity test has been performed. In this case a rainfall event of 20 mm is distributed in 1, 2, 4, 8 and 16h (corresponding rainfall intensities of 20, 10, 5, 2.5 and 1.25 mm/h). The results obtained for the Crecora and Kilmallock sites are presented in Figure 5.5 and 5.6 respectively. In both cases, short and intense events lead to a peak of infiltration and runoff, with most of the water volume being evacuated as runoff. In contrast, the lower intensity and prolonged rainfall events generate similarly long infiltration events with ponding, which enhances the cumulative infiltration but reduces runoff significantly. Hence, surface runoff is not generated for rainfall intensities significantly lower than the threshold values found at hourly resolution. In this way, the 4h rainfall event - with a corresponding rainfall intensity of 5 mm/h - does not lead to surface runoff in the Crecora site, which had an estimated infiltration capacity of 6.5 mm/h (Figure 5.5 c). Similarly, runoff is just generated for the 1h rainfall event in the Kilmallock site (20 mm/h) as it had an estimated infiltration capacity of 12 mm/h (Figure 5.6 c).

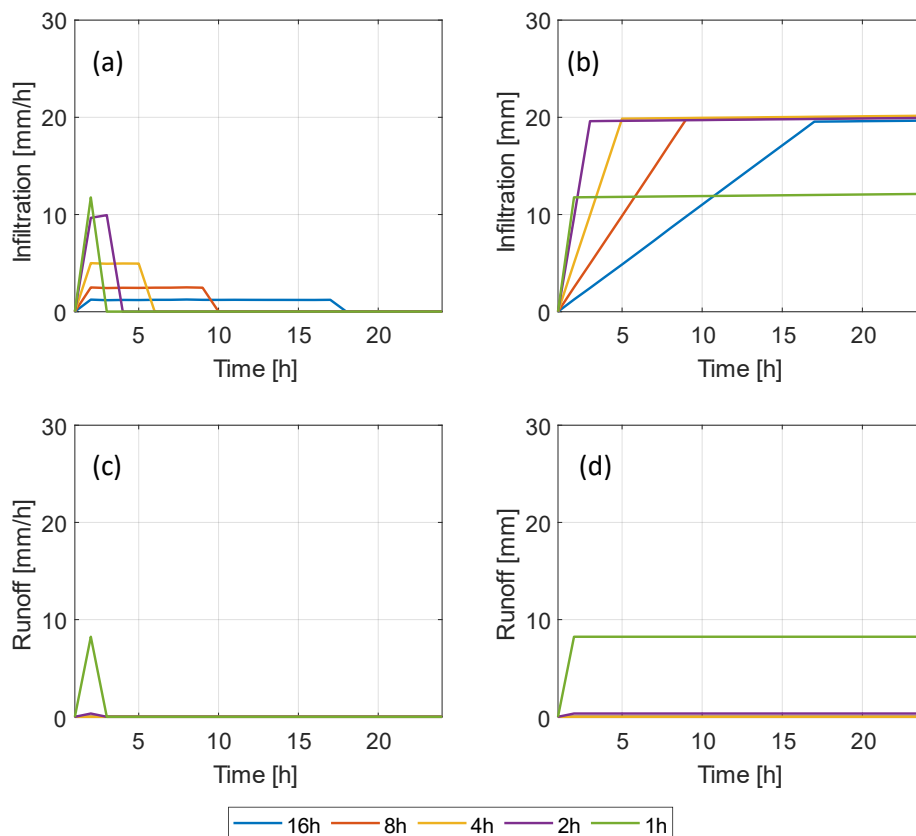


Figure 5.6: Infiltration rate (a), and cumulative infiltration (b), generated from 100mm rainfall distributed in 1h (green), 2h (purple), 4h (yellow), 8h (orange) and 16h (blue) events and the corresponding runoff generated (c), and total runoff (d) at the Kilmallock site.

5.4 Conclusions and Discussion

In this chapter, the importance of the processes involved in the infiltration through the unsaturated zone are analysed. Firstly, the importance of the soil moisture budget parameters has been evaluated by assessing the impact (and suitability) of the chosen PE estimation method for the selected study catchments, as well as the effect of changing rainfall intensities and seasonality. Secondly, the infiltration capacity of the two additional study sites has been assessed by modelling of the vadose zone processes with the Hydrus software (Simunek et al. 2009).

The comparison of three commonly used PE estimation techniques with the data obtained from Met Eireann has revealed the sensitivity of the Penman-Monteith to the net radiation estimation, as the PE obtained from calculated radiation values differ from the Met Eireann time series used as reference for the Mattock and the Dripsey. However, the results suggest that this is not always the case, as the cycle obtained for the Nuenna catchment is almost identical to that estimated with the reference data. The Blaney-Criddle method appears to overestimate PE significantly through all the year. These results, however, are not surprising as the Blaney-Criddle method relies on temperature data only, which is less related to evapotranspiration than solar radiation. The results show, therefore, that the Hargreaves equation is generating the closest PE estimates to the Met Eireann values for the Mattock and the Dripsey. Moreover, the simplicity of the variables required for its calculation represent an advantage when estimating PE under future climate scenarios, as temperature projections are considered to be robust, and introduce less uncertainty than other variables required for other methods such as air moisture content. Nevertheless, the application of this approach under future climate scenarios assumes that the expressions to estimate the radiation term remain valid. Hence, the Hargreaves equation will be used to estimate PE values on the climate change impact assessment (Chapter 9). Finally, the modified rainfall time-series used in the sensitivity analysis (Chapter 4) have also been used here to test the sensitivity of the soil moisture budget parameters.

The results obtained from the soil moisture budget suggest that any changes in rainfall intensity and/or seasonality would have a larger effect on infiltration than AE. This is because, in the Irish context, AE occurs at the prevailing PEthe potential rate from October to May approximately, so any alteration of the rainfall patterns would have little effect on the monthly AE during this period. The results obtained also indicate that an increase in either

rainfall intensity or seasonality would lead to an enhanced infiltration. Nevertheless, these results should be compared with other modelling approaches that would measure the changes in actual recharge.

The implementation of the Hydrus 1-D in the two additional sites has resulted, firstly, in the estimation of the soil characteristic parameters. These parameters have then been used to approximate the soil infiltration capacity within the considered areas. The contrasting results obtained by running the calculations at daily and hourly time steps have highlighted the importance of the temporal discretization resolution.

The infiltration capacity has been estimated in 6.5 mm/h for the Crecora site, and 12 mm/h at the Kilmallock, which would constitute relatively intense rainfall events. These results can be explained by the high saturated hydraulic conductivity values, that makes the model less sensitive to other parameters such as soil thickness and water table position. These results would suggest that the saturated hydraulic conductivity is the main controlling factor in moderately to high permeability soils. It is likely that other soil parameters mentioned above would gain importance in lower permeability subsoils.

Both sites are on moderately permeable soils with associated recharge coefficients of 60%, overlying carbonate aquifers, according to the national recharge map (Hunter Williams et al. 2013). Hence, the results obtained suggest that there is a dominance of the infiltration processes in the locations where the recharge coefficient is 60% or higher as long as the aquifer is able to accept these large volumes of water. Further investigation on other sites with similar and lower recharge coefficients is required in order to establish a relationship between infiltration capacity and recharge coefficients. Furthermore, as has been shown in Chapter 4, the aquifer's storage capacity is the main groundwater recharge constraining factor. Hence, an integrated modelling of the study catchments (i.e. Nuenna, Mattock and Dripsey), combining Hydrus 2D and recharge estimations, would be necessary to link the effect of rainfall intensities (recharge coefficients) and the aquifer's storage capacity (recharge caps), as a better understanding of such relationships could contribute to better climate change impact assessments.

6. Recharge Characterisation at Catchment scale

6.1. Introduction

The quantification of groundwater recharge is an essential requirement for efficient groundwater resources management and yet, one of the most difficult factors to measure in groundwater resources assessments (Sophocleous 1991). The direct measurement of recharge rates is not possible and, therefore, needs to be approximated by different calculation techniques (Risser et al. 2005). Due to the high uncertainties associated with these calculations, it is recommended - and common practice - to quantify groundwater recharge by applying multiple techniques and comparing the results to assess their validity and compensate their flaws (Healy 2010) (see Section 2.1).

In the context of climate change, groundwater resources can be directly affected by changes in recharge rates and patterns, but also indirectly due to a change in the way of using them, as well as their intensity of consumption (Taylor et al. 2013). For instance, if hydrologic droughts become more frequent, the exploitation of groundwater resources – that are naturally buffered due to their large storage capacity of the aquifers in proportion to the surface water bodies – would intensify. Additionally, an increase in population would lead to a similar result of increased consumption. Furthermore, changes in land use, agriculture, etc could also affect the usage of groundwater resources. In humid areas, where aquifers are often full, groundwater recharge is often governed by the capacity of the aquifer to accept further recharge (Scanlon et al. 2002). Hence, robust assessments of the aquifer's storage capacity are necessary to evaluate the possible impacts of a changing climate, as extreme events are expected to become more frequent.

In Ireland, where almost 65% of the aquifers are regarded as poorly productive, the limited storage capacity of the aquifers has typically been approximated by the application of recharge caps (See Section 2.1 and Chapter 4). The IWGGW (2005b) suggested that poor and locally important aquifers should have recharge caps of 100 mm/y and 200 mm/y, respectively, in order to represent their limited storage capacity. Once this capacity is surpassed, 'rejected recharge' occurs and the excess of infiltration is lost as overland flow or interflow. The recharge caps approach was applied to generate a national recharge map by

Hunter Williams et al., (2013) where these recharge caps are used to estimate the groundwater resources that are available for long-term and sustainable abstraction (Section 2.1).

Specific yield (S_y) has been typically calculated through pumping tests. Nevertheless, in fractured aquifers hydraulic properties vary drastically within short distances. Moreover, the characteristic properties of fractured aquifers are not just translated into high heterogeneity and anisotropy of the hydraulic properties, but also into a scaling effect of these properties. Thus, the use of site-specific measurements may not be representative of an entire catchment.

Recharge methods based on water table fluctuation approaches can also be used to evaluate the changes in storage within unconfined aquifers (Healy and Cook 2002). For instance, this approach can be used to assess multiannual changes by comparison with historical values (Ruud et al. 2004). Maréchal et al. (2006) used a “double water table fluctuation” (DWTF) to estimate both recharge and specific yield in a semi-arid region by aggregating seasonal (dry-wet) water budgets. Similar approaches have been applied in India (Machiwal and Jha 2015; Chinnasamy et al. 2018).

In this chapter, a recharge characterisation for the Mattock and Dripsey catchments (see Figure 3.1) is presented. The approaches applied include: the water table fluctuation method (WTF), baseflow separation, Dupuit-Forchheimer calculations, and the implementation of the NAM rainfall-runoff model. The objective of this recharge calculation exercise is two-fold: (1) to constrain the annual recharge uncertainty within the study areas and (2) to use the recharge estimations as a proxy to assess the storage capacity of the aquifer. The range of annual recharge values obtained are used to calculate S_y by inverting the WTF equation. Therefore, an *effective* S_y value is calculated at catchment scale, which is more sensible in terms of groundwater resources management.

6.2. Methods

This section outlines the range of methodologies used to approximate groundwater recharge and assess the transmissivity of the aquifers underlying the study areas. For this purpose, the available datasets presented in Sections 3.2.2 and 3.2.3 have been used in the recharge

estimations for the Mattock and the Dripsey respectively. The Mattock is a small catchment (17 km²) underlain by a poorly productive metasedimentary aquifer (see Section 3.2.2.1) whilst the Dripsey is a relatively large catchment (82 km²) underlain by Devonian Sandstones (see Section 3.2.3.1).

The reports provided by the EPA (CDM and OCM 2010a,b) contain the data corresponding to an integral geophysical survey, and pumping and recovery tests for both catchments, with their corresponding horizontal hydraulic conductivity estimations. Even though the data from the geophysical survey has not been directly used in these calculations, it has provided valuable information for the results interpretation. The pumping and recovery tests, and hydraulic conductivity estimations have been used to approximate the aquifers' transmissivity (Section 6.2.6). Furthermore, the former has also been used to approximate groundwater recharge with the Dupuit-Forchheimer equation (Section 6.2.5).

6.2.1. Recharge Coefficient Approach

As a first approximation, the recharge coefficient approach presented in Chapter 2 (and tested in Chapter 4) has been applied for the two study catchments for the period 2012-2015. As presented previously (Section 2.1.1), this method consists of applying a soil moisture budgeting technique, and then multiplying the outputs by a set of recharge coefficients that represent the percentage of effective rainfall becoming actual recharge (Misstear et al. 2009a; Hunter Williams et al. 2013). These coefficients reflect the hydrogeological settings of a specific area based on local properties such as soil and subsoil permeability or vulnerability category (See Table 2.1).

6.2.2. Water Table Fluctuation

After a rainfall event, water percolates through the unsaturated zone to the water table causing a variation in the groundwater levels. The water table fluctuation method is based on the premise that, in the absence of rainfall -and recharge- the water levels decrease progressively following a recession curve, which has a characteristic slope and shape for each aquifer. However, each new precipitation event leads to the rise of the water table from which recharge can be calculated. Simplifying, the amount of water contributing to recharge corresponds to the fluctuation caused by the rainfall event multiplied by the Specific Yield (S_y) (Healy and Cook, 2002). However, this approach assumes that lateral inflows and

outflows balance one another during the period considered, and that there are no significant groundwater abstractions.

For this study, the methodology presented by Crosbie et al. (2005) has been applied at hourly time steps, with some modifications to adapt it to the local hydrogeological settings. This technique was chosen because it is based on a continuous time series approach rather than an event-based one. Furthermore, this methodology had already been applied in Ireland (Cai and Ofterdinger 2016) in a similar context. The model presented by Crosbie et al. (2005) is described by Eq.6.1:

$$R_t = \begin{cases} [(h_t - h_{t-1}) + D(z)\Delta t]S_{ya} & \text{if } \begin{cases} [(h_t - h_{t-1}) + D(z)\Delta t] > 0 \\ \sum_{t > t' > t-\alpha} P_{t'} > 0 \\ h_t < h_{t+\beta} + D(z)\Delta t \end{cases} \\ 0 & \text{otherwise} \end{cases} \quad (6.1)$$

where R_t is recharge at time t , h_t is water level at time t , $D(z)$ is the drainage rate, S_{ya} is the apparent specific yield, P_t is precipitation at time t , α is a precipitation time parameter representing the time lag between a rainfall event and the rise in the groundwater levels and β is the Lisse effect parameter.

Equation 6.1 shows that groundwater recharge can be calculated by multiplying the water table increment by the apparent specific yield (adjusted at each time step) where the difference between the drainage term and the water level rise is greater than 0. It also accounts for the response time of the aquifer (α) and the Lisse effect that can take place in shallow aquifers after intense rain events.

Three main modifications were made from the original method: 1) constant S_y values have been used rather than apparent S_y due to of the uncertainty of this parameter in the fractured bedrock aquifers investigated here; 2) instead of fitting a linear trend to calculate the drainage term as a function of the water table level, the median value for each water table depth band has been taken (Figure 6.1); and 3) the Lisse effect has been neglected due to the depth of the observation boreholes, since it is considered to occur only in areas where the unsaturated zone is thinner than 1-1.3m (Weeks, 2002). Furthermore, even though the

Lisse effect can also occur in fractures, it is more common in shallow unconsolidated aquifers where primary porosity is predominant.

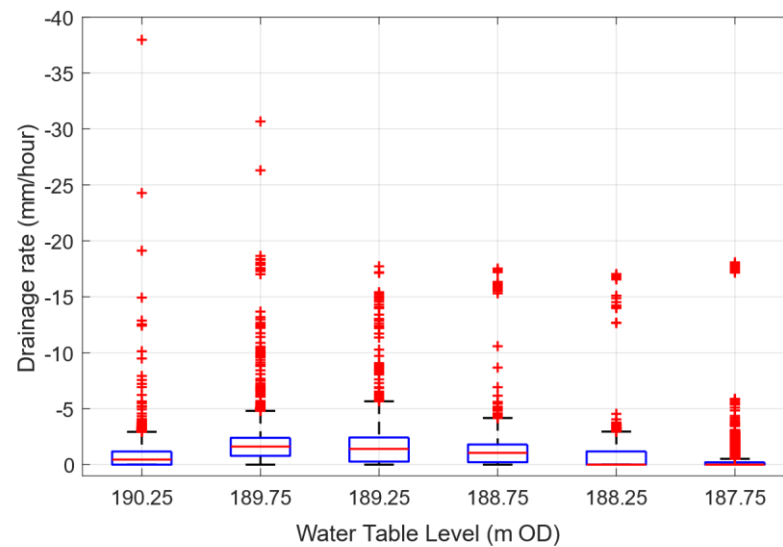


Figure 6.1: Boxplot of the drainage rates as a function of the water table level for the DR1-Shallow borehole (Dripsey catchment).

The steps applied to calculate groundwater recharge as described in Crosbie et al. (2005) are:

1. Apply a low-pass fast Fourier transform (FFT)
2. Calculate hourly increments
3. Estimate and add the drainage term
4. Remove all negative terms
5. Remove the terms not preceded by rainfall in the response time (α), which is estimated by a lagged cross correlation.
6. Multiply the signal created by the S_y
7. Aggregate recharge estimations in monthly and yearly values

The application of the FFT allows the de-noising of the time series to be and removes - or minimize - of the groundwater rises that are not caused by rainfall infiltration but by other sources such as tides, pumping or the transducer (step 1). The drainage term accounts for the water table losses by evapotranspiration or lateral flows (step 2). Hence, if for a given increment the subtraction of the corresponding drainage term results in a negative term, it implies that recharge does not occur, and so this term must be removed (step 4). To further minimize the presence of groundwater rises not caused by recharge, all the rises not preceded by rainfall within the system's response time are removed (step 5). Once the

groundwater signal is de-noised, the rises can be multiplied by the S_y to calculate recharge (step 6) and aggregated (step 7). The steps followed are illustrated in Figure 6.2.

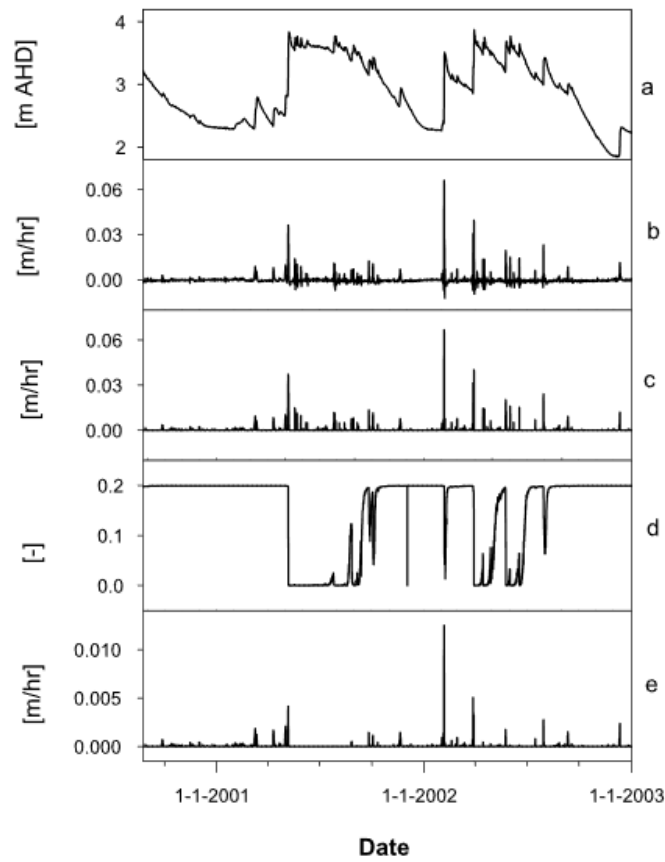


Figure 6.2: Recharge calculations from Crosbie (2005): (a) Water level signal in meters above Australian Height Datum (mAHD) (b) Differenced water level signal (m/hr); (c) Water level rises contributing to recharge (m/hr); (d) Apparent specific yield. (e) Recharge signal (m/hr).

Finally, Eq.6.1 was inverted in order to estimate an effective S_y for the catchments based on the range of annual groundwater recharge values obtained by applying all the calculation methods outlined in this section, following a similar approach to Tedd et al., (2012). The results are presented in Section 6.3.7.

6.2.2.1. Time series analysis: Cross-correlation and autocorrelation

Cross-correlation represents the relationship between two signals, in this case, between rainfall and groundwater levels. Because the rainfall signal is an uncorrelated event, the cross-correlation function obtained will represent a pulsive response of the aquifer (Padilla and Pulido-Bosch 1995; Larocque et al. 1998; Lee et al. 2005). Hence, the response time of the aquifer can be estimated by applying a lagged cross-correlation, where the delay

corresponds to the time between lag = 0 and the maximum correlation. The cross-correlation is mathematically defined as:

$$C_{xy}(k) = \frac{1}{n} \sum_{t=1}^{n-k} (x_t - \bar{x})(y_{t+k} - \bar{y}) \quad (6.2)$$

$$r_{xy}(k) = \frac{C_{xy}(k)}{\sigma_x \sigma_y} \quad (6.3)$$

where C_{xy} is the cross-correlogram, n is the length of the time-series, x_t and y_t are the two time-series examined at a time t , and $\bar{x}$ and $\bar{y}$ their corresponding mean; $r_{xy}(k)$ is the cross-correlation coefficient, and σ_x and σ_y are the standard deviations of the time series.

The autocorrelation of a variable can be defined as the correlation of a signal with itself at different times. Consequently, the autocorrelation of a process, represents the correlation between values of a process in different moments. In hydrogeological studies it has frequently been described as measure of the linear dependency over a time period (Larocque et al. 1998) that can be used to examine the “memory effect” of the system (Mangin 1984; Angelini 1997). Thus, the inter-dependency of the time series can be easily assessed with the velocity of the correlation to reach 0; If the decrease is by a long smooth slope the system is highly dependent, while a sharp drop below the x-axis is characteristic of uncorrelated time series such as rainfall. Autocorrelation can be mathematically expressed as:

$$C(k) = \frac{1}{n} \sum_{t=1}^{n-k} (x_t - \bar{x})(x_{t+k} - \bar{x}), k \geq 0 \quad (6.4)$$

$$r(k) = \frac{C(k)}{C(0)} \quad (6.5)$$

where $C(k)$ is the correlogram, n is the length of the time-series, x_t is the value of the variable x at a time t , and $\bar{x}$ the mean; k is the time lag and $r(k)$ is the autocorrelation function.

6.2.3. Baseflow Separation

Hydrograph analysis can provide valuable insights on a specific catchment as its shape depends on the physical characteristics of the catchment and the meteorological conditions.

One of the most interesting applications from the hydrogeological point of view is the hydrograph separation into its flow components. In Ireland, the flow pathways have been conceptually divided into: overland flow, interflow, shallow and deep groundwater flows for poorly productive aquifers as represented in Figure 2.2 (Section 2.2). Hence, overland flow and interflow occur within the surface and overburden – which is typically formed by glacial deposits – whereas the shallow groundwater flow - or fast response - takes place within the transition zone and upper bedrock, and the slower response of the aquifer - or deep groundwater flow - corresponds to the flow through the deeper bedrock.

The hydrograph observed is the result of the addition of the flow components described above. Therefore, it is possible to estimate the groundwater contribution (discharge) to the river flow, by separating its component from the hydrograph. When this method is applied to annual or multiannual time series, it can be used as a proxy for groundwater recharge by the principle of conservation of mass. However, it is known that this technique can substantially underestimate groundwater recharge since it is assumed that any other losses of groundwater such as lateral flows to other aquifers, abstractions from wells or evapotranspiration from shallow water tables are considered negligible. In other words, the aim of the baseflow separation is the identification of the portion of discharge stemming from groundwater flow (Figure 6.3). The groundwater contribution is usually expressed as a ratio of the total discharge, defined as the base flow index (BFI) (Institute of Hydrology 1980).

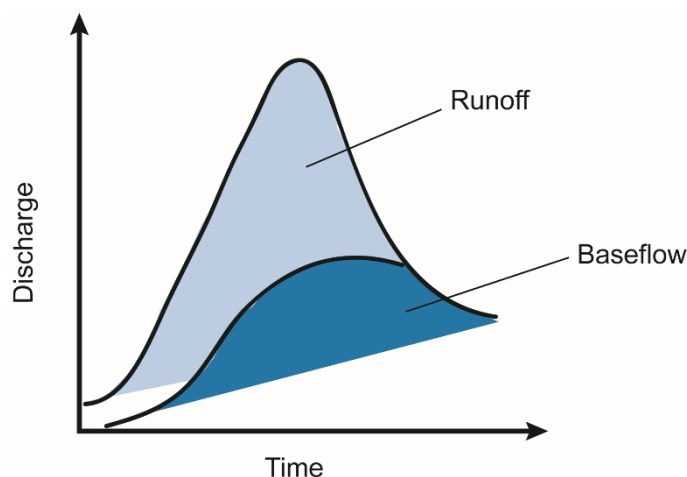


Figure 6.3: Schematic of the baseflow component within a hydrograph.

There are several methods to estimate the BFI of a hydrograph based on different principles: from relatively simple graphical methods to recession analysis and flow duration curves. As in all calculations, the choice of the technique depends on the purpose of the study and

available data. In this project, the software BFI+ 3.0 (Gregor 2010) was used as it includes 11 separation methods, and it provided a simple implementation and comparison of the different techniques. The three methods of Sloto and Crouse (1996) (fixed interval, sliding interval and local minimum methods) were dismissed as the results obtained were considered unrealistic given the “*squared*” geometries of the baseflows. For the remainder of the algorithms and digital filters, all the methods that include three or more parameters to calibrate were also discarded to reduce uncertainty. Hence, a first run was performed for the methods presented below to assess their performance in the study areas:

- One-parameter algorithm (Chapman and Maxwell 1996)
- Two-parameter algorithm (Boughton 1984; Chapman and Maxwell 1996)
- EWMA filter (Tularam and Ilahee 2007)
- Chapman algorithm (Chapman 1991; Mau and Winter 1997)
- Eckhardt filter (Eckhardt 2005)
- BFLOW (Lyne and Hollick 1979; Nathan and McMahon 1990)

Subsequently, a simple analysis of the outcomes following the general rules presented in Merz et al. (2009) which can be summarised as:

1. Low flow conditions before the beginning of a flooding event consist entirely of baseflow.
2. The rapid increase of the river level in comparison to the groundwater levels in the vicinities leads to bank storage. The lag caused by the return of the stored water to the river generates a baseflow recession after the total peak in the hydrograph.
3. Baseflow peaks after the hydrograph because of the lag caused by the flow through the aquifers.
4. The baseflow recession is most likely to follow an exponential decay.
5. The baseflow will behave as the rest of the hydrograph components as soon as the quick flows stop.

The application of these rules led to the dismissal of the two-parameter algorithm, the EWMA and BFLOW filters. A more detailed calibration process and analysis was carried out for the remaining filters (One-parameter algorithm, Chapman algorithm and Eckhardt filter), which was combined with the previous knowledge of the catchments. The results showed that both

the One-parameter and the Chapman algorithms were overestimating the baseflow when compared to prior baseflow estimations (O'Brien 2013) or would represent unrealistically high BFI values (over 40%) . In fact, O'Brien et al. (2013b) modified the BFLOW (Lyne and Hollick 1979) algorithm for a better separation of the hydrograph in the flow components described previously. It is possible, however, that implementation of different versions of a similar algorithm would lead to contrasting performances.

Hence, the Eckhardt recursive digital filter (Eckhardt 2005) was implemented according to the equation:

$$B_{k+1} = \frac{(1 - BFI_{max}) \cdot \alpha \cdot B_k + (1 - \alpha) \cdot BFI_{max} \cdot Q_{k+1}}{1 - \alpha \cdot BFI_{max}} \quad (6.6)$$

where α is the baseflow filter parameter (0.98 by default) and BFI_{max} represents the maximum value of long-term base-flow index (BFI). The α parameter can be adjusted by a recession analysis. Eckhardt (2005) also proposed predefined values of BFI_{max} depending on the hydrogeological settings; a value of 0.25 is suggested for perennial streams with hard-rock aquifers, so this was taken as the initial value. However, given that this value controls the maximum baseflow percentage, this parameter was evaluated to determine an optimal value, based on previous knowledge of the catchments.

6.2.3.1. Calibration

The digital recursive filter used in this study has two parameters in the equation that need to be calibrated. First, the calculation of the α parameter (Eq. 6.6) was carried out by the 5-day recession analysis as described in (Eckhardt 2005), and three likely values were obtained for each case: best fit and the two values representing the 95% interval of confidence.

It is acknowledged that the BFI_{max} parameter introduces a certain subjectivity to the calculation since this parameter cannot be derived from streamflow data and therefore, has a larger uncertainty associated with it (Eckhardt 2012). For this reason, it is proposed to compare it with other methods. Eckhardt (2005) assessed how the errors and uncertainty of these two parameters can affect the baseflow estimations. In a first study, an experimental sensitivity analysis was carried out, and the results suggested that the BFI_{max} parameter had a larger effect than the parameter α . However, Eckhardt (2012) proved by an analytical

sensitivity analysis that the error induced by the recession constant had a larger effect than the BFI_{max} parameter, since the recession constant would cause a larger relative error.

In the present study, the calculated baseflow values were compared to the observed water table levels in the recharge area, as suggested in Misstear and Fitzsimons (2007), and to previous similar studies (when available) in order to adjust the BFI_{max} parameter.

6.2.4. NAM rainfall-runoff modelling

The “Nedbor-Afstromnings-Model” or NAM was developed by the Department of Hydrodynamics and Water Resources at the Technical University of Denmark (Nielsen and Hansen 1973). It is a deterministic, lumped and conceptual rainfall-runoff model that is integrated as a module of the MIKE11 river modelling package that simulates runoff as well as the different variables of the water cycle from meteorological inputs.

This rainfall-runoff model generates runoff simulations from the input rainfall and potential evapotranspiration (PE) at daily time-steps, while observed discharge is used for calibration purposes. In cases of small or ‘flashy’ catchments such as the Mattock, higher resolution meteorological datasets may be needed to achieve a good calibration. Given that, in the context of the two study catchments, there was no need to simulate snow storage and melting, so no further meteorological inputs were required.

This model can be applied for the entire area of study or to create divisions to simulate the water cycle for different sub-catchments. In this case, the NAM model has been applied to the entire catchments as this approach is more suitable for the purpose of this recharge characterisation, but also due to the lack of available data to perform a higher resolution modelling. The NAM includes a sequence of four reservoirs that represent: snow storage, surface storage, root zone storage and groundwater storage. Additionally, the baseflow component can be subdivided into shallow and deep to reproduce the faster and slower groundwater responses. The resulting runoff is separated into overland flow, from soil moisture excess in the surface storage, interflow from the second storage, and finally the baseflow from the deep storage (O’Brien et al. 2013a). The structure of the model is presented in Figure 6.4.

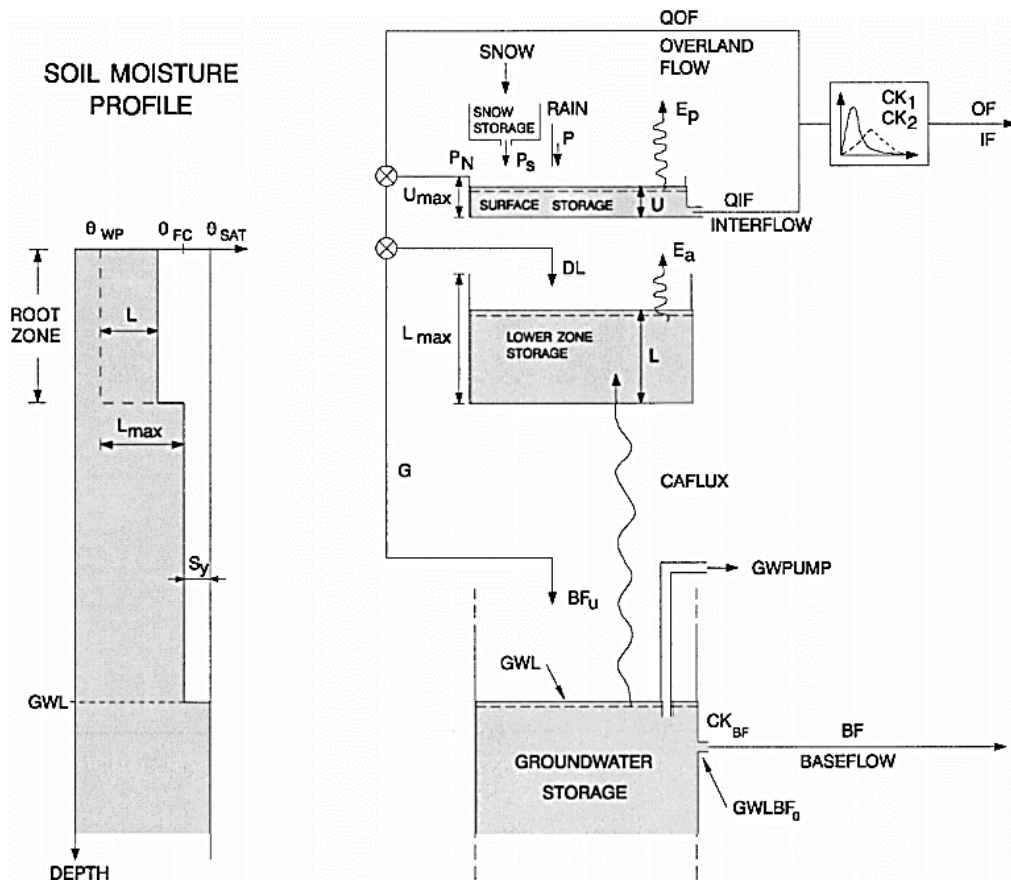


Figure 6.4: Structure of the NAM model (source: Madsen 2000)

As in most rainfall-runoff models, NAM is based on a sequence of interconnected reservoirs that approximate the physical processes observed in nature. Each one of these reservoirs represents one part of the system, from the subsoil and overflow generation (first reservoir) to deep groundwater flow and storage (last reservoir). The flow from one reservoir to another is governed by threshold parameters that can be calibrated, while the flow routing is controlled by non-linear equations with constants that can also be adjusted. There is a total of 11 parameters to be calibrated.

As rainfall occurs, the upper reservoir fills up until reaching a maximum level fixed by the U_{max} parameter, which represents the cumulative total of water content of the interception storage and overall storage in the uppermost layers. Simultaneously, actual evaporation (AE) occurs at potential rate, depending on the readily available water. A part of the excess water from this first reservoir is released as interflow (QIF), and another part infiltrates into the lower and groundwater storages. The lower storage presents a similar structure to the

upper, and it represents the soil moisture and root zone storage available for vegetation (L), where the losses are represented by AE , which is proportional to the state of the lower reservoir. Overland flow (QOF) occurs when both the upper and lower storages reach their capacity (U_{max} and L_{max} respectively). This flow is transmitted through a linear reservoir governed by a routing time constant CK . Furthermore, the parameters TOF, TIF and TG represent thresholds that must be exceeded by the L/L_{max} relationship in order to generate interflow, overland flow and recharge respectively.

The excess flow then infiltrates to the shallow and deep groundwater storages to simulate baseflow that can be further divided into shallow groundwater flow ($QSGW$) and deep groundwater flow ($QDGW$). These flows are controlled by two different time constants for routing baseflow: $CQBF$ for the shallow groundwater, and CK_{Low} for the deep groundwater. The former also defines the proportion of groundwater recharge to each of the groundwater reservoirs.

The NAM model was selected to simulate groundwater recharge based on different criteria, as follows.

(1) The simplicity of its inputs: as for as in other rainfall-runoff models (e.g. HBV, SWAT, IACHRES, GR4J), NAM requires just rainfall and PE as inputs, together with discharge time series for the calibration. Data availability is a common constraint in hydro(geo)logical studies, and it is particularly important in climate change impact studies. Because in this thesis the selected rainfall-runoff model will also be used in this thesis used in Chapter 9 to assess the possible impacts of climate change on groundwater resources, it is of crucial importance that the inputs of such a model are few and simple (i.e. not derived from other variables), in order to reduce the amount of associated uncertainty.

(2) The complexity of the model: typically, the more complex the model, the more inputs are required, and the more parameters needed for calibration. Despite the issues linked to the data requirements discussed above, complex models with many parameters (e.g. HSPF) can lead to overparameterization and equifinality issues. Hence, it is necessary to select a parsimonious model that is complex enough to represent the local physical processes, but as simple as possible to avoid the above-mentioned problems.

(3) Capacity to reproduce the local hydrogeological processes: PPAs are highly complex aquifers with a clearly distinct behaviour between the shallower part of the aquifer (Transition Zone) where the bedrock is weathered and fractured, and the deeper part where fractures are sparser and less connected. For this reason it was considered important that

the chosen model could be able to simulate the shallow and deep groundwater flows (fast and slow response) separately, instead of one single baseflow as is more common in rainfall-runoff models (e.g. HBV, HSPF, SWAT, GR4J, IACHRESS.)

(4) Suitability to the Irish climate: each hydrological model represents the runoff generated by different mechanisms. Given the humid Irish climate, it is reasonable to discard those models based on runoff generation by excess of infiltration (i.e. SWAT, TOPMODEL) as overland flow typically occurs by excess of saturation in this context.

(5) Previous application in Ireland: the successful application of a model within Ireland, indicates the suitability of the model structure for Ireland. The NAM model was previously applied to several Irish catchments (RPS 2008), including catchments underlain by PPAs such as the Mattock catchment (RPS 2008; O'Brien et al. 2013a).

6.2.4.1. Calibration

Two different objective functions are used to assess the performance of NAM when simulating runoff. Firstly, the Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe 1970) is calculated to evaluate the goodness of fit of the simulated discharge values:

$$R^2 = \frac{\sum(Q_{obs} - Q_{sim})^2}{\sum(Q_{obs} - Q_{mean})^2} \quad (6.7)$$

where Q_{obs} is the observed discharge, Q_{sim} the simulated discharge and Q_{mean} the overall mean of the observed discharges. The R^2 value represents the goodness of fit, where 1 is a perfect fit while an R^2 value of 0 indicates that the model performs as well as the average of the measured discharges. Finally, NSE negative values would suggest that the mean of the observed discharge would perform better than the model.

In the recent years some authors have highlighted the shortcomings of this approach. Gupta et al. (2009), demonstrated that discharge variability is not properly considered within the NSE and proposed a new criterion, the Kling-Gupta efficiency (KGE), which can be mathematically expressed as:

$$E_{KG} = 1 - \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\alpha - 1)^2} \quad (6.8)$$

Where r is the Pearson correlation coefficient that assesses the shapes and timing errors:

$$r = \frac{cov(Q_o - Q_s)}{\sigma_o^2 \sigma_s^2} \quad (6.9)$$

where cov is the covariance between observed discharge (Q_o) and simulated discharge (Q_s) and σ is the standard deviation. The term β evaluates the bias between observed and simulated flows:

$$\beta = \frac{\bar{Q}_s}{\bar{Q}_o} \quad (6.10)$$

where the $\bar{Q}_s$ and $\bar{Q}_o$ are the mean simulated and observed discharge respectively. Finally, the α term evaluates the flow variability error and is the ratio between the simulated and observed standard deviations:

$$\beta = \frac{\sigma_s}{\sigma_o} \quad (6.11)$$

Similarly to the NSE the values of the KGE range from 1 for a perfect fit to $-\infty$.

6.2.5. Dupuit-Forchheimer calculations

Like the baseflow separation, several other recharge calculation methods rely on the same principles of the conservation of mass and the continuity equations. For instance, a simple approach to estimate groundwater recharge within an aquifer would be to estimate the throughput capacity if a steady state is assumed. Whereas for confined aquifers, the Darcy equation can be combined directly with the continuity equation, the solution for unconfined aquifers should include the Dupuit-Forchheimer assumptions (Misstear et al. 2017). These assumptions hold that the vertical component of the groundwater flow in an unconfined aquifer is negligible, and that the hydraulic gradient is equal to the slope of the water table. These conditions are rarely fulfilled in real cases due to the presence of abstractions or other water bodies. Nevertheless, the Dupuit-Forchheimer assumption can still be applied to approximate groundwater recharge within a catchment by using the equation:

$$w = \frac{K(H_o^2 - H_L^2)}{L^2} \quad (6.12)$$

where K is the hydraulic conductivity, H_o and H_L are the water levels above the base of the aquifer at the water divide and discharge area, respectively, and L represents the distance between the groundwater divide and the discharge point.

As with all the techniques, this method presents its own limitations that must be taken into consideration when interpreting the results. Firstly, it assumes annual uniform recharge and so, to account for the seasonal variability with this approach, water level measurements at different seasons are required. Secondly, it ignores the seepage face at the downgradient end of the flow system (the river). Finally, it is difficult to account for heterogeneity in aquifers dominated by secondary porosity where the hydraulic conductivity values are extremely variable.

6.2.6. Transmissivity estimations

Aquifer tests, in general, are an extended practice to estimate aquifer properties such as hydraulic conductivity, transmissivity and the aquifer's storage capacity. The most common types of aquifer tests are pumping and recovery tests.

6.2.6.1. *Pumping and Recovery Tests: Cooper -Jacob solution*

Theis (1935) developed the classic equation for transient flow in wells which relates the drawdown from the pumping rate, the transmissivity and the storativity of an aquifer with the expressions:

$$s = \frac{Q}{4\pi T} W(u) \quad (6.13)$$

$$u = \frac{r^2 S}{4Tt} \quad (6.14)$$

where s is the drawdown, u is a dimensionless parameter, Q is the pumping rate in the well, T and S are the transmissivity and storativity of the aquifer, respectively, r is the distance from the pumping well to the observation point, t is the time since pumping began and $W(u)$ is the Theis well function:

$$W(u) = -0.5772 - \ln u + u - \frac{u^2}{2 \cdot 2!} + \frac{u^3}{3 \cdot 3!} - \frac{u^4}{4 \cdot 4!} + \frac{u^5}{5 \cdot 5!} \dots \quad (6.15)$$

During a pumping test, the drawdown (s), pumping rate (Q), distance (r) and time (t) are known and they can be used to determine T and S . The most common way of estimating these parameters is the graphical technique. This consists on matching the curve obtained by plotting the observed drawdown (s) against t (or against t/r^2 if there are data for several observation boreholes) on a log-log paper with the Theis curve type (obtained by plotting $W(u)$ against $1/u$).

The Cooper-Jacob solution (1946) for interpreting recovery tests is a simplification of the Theis method (1935) for the condition of long pumping time and small values of radial distance i.e. for small value of the function u . When these conditions are fulfilled, the expansion series of the $W(u)$ term in the Theis equation can be neglected after the two first terms. Under these conditions the Theis equation can be approximated to:

$$s = \frac{2.30Q}{4\pi T} \log \left(\frac{2.25Tt}{r^2 S} \right) \quad (6.16)$$

where, T and S are the transmissivity and Storativity respectively, Q is the pumping rate, s is the drawdown, t_0 is the intercept on the time axis where drawdown equals zero and r is the distance between the pumping and the observation wells.

Similar to the Theis Recovery method, the Cooper-Jacob solution involves fitting a linear trend to the observed drawdown data, which are plotted against the logarithm of the time since the start of the recovery. Once the straight line is fitted, the properties of the aquifer (transmissivity and storativity) can be estimated following the expressions:

$$T = \frac{2.30Q}{4\pi \Delta s} \quad (6.17)$$

$$S = \frac{2.25T t_0}{r^2} \quad (6.18)$$

Further information on these methods can be found in texts such as Kruseman et al. (1990) and Misstear et al. (2017).

6.3. Results

6.3.1. Recharge Coefficient Approach

The results obtained by applying the GIS-based tool described in Section 6.2.1 to the two study catchments are presented in this section.

The estimated annual average rainfall over the Dripsey in the study period of 2012-2015 is 1121mm. Most of the Quaternary deposits are classified as moderately permeable subsoils; there are also till-derivate subsoils and peat in the upper catchment and on the borders according to the National Recharge Map (Hunter Williams et al. 2013). As a result, there is a large range of recharge coefficients in the catchment (20 - 85%) and, consequently, a significant range in potential recharge estimations (182-688 mm/y). Nevertheless, the catchment is underlain by Old Red Sandstones, classified either as Locally Important aquifers or moderately productive only in Local zones (LI) which have an associated recharge cap of 200 mm/y.

Figure 6.2a presents the annual recharge estimation over the Dripsey catchment. As can be observed, the recharge value is 200 mm/y for most of the catchment. Only the areas corresponding to peat and alluvium - which have associated low recharge coefficients - present lower recharge values ranging between 152- 182 mm/y.

In the case of the Mattock, the average annual effective rainfall is about 450 mm/y. The majority of subsoils in the Mattock are poorly drained tills, however there are some outcrops in the higher parts of the catchment, together with well drained sands and gravels along the valley upstream. This translates into a large range of recharge coefficients (7.5% – 85%). However, the Mattock catchment is underlain entirely by poor aquifers, which according to the GSI are classified as (1) poor aquifers which are generally unproductive except for local zones (PI), and (2) poor aquifers which are generally unproductive (Pu). Both categories have an associated recharge cap of 100 mm/y which is applied through all the catchment. As a result, a fairly homogenous recharge estimation of 100 mm/y is obtained with exception of few low permeability areas (Figure 6.5b).

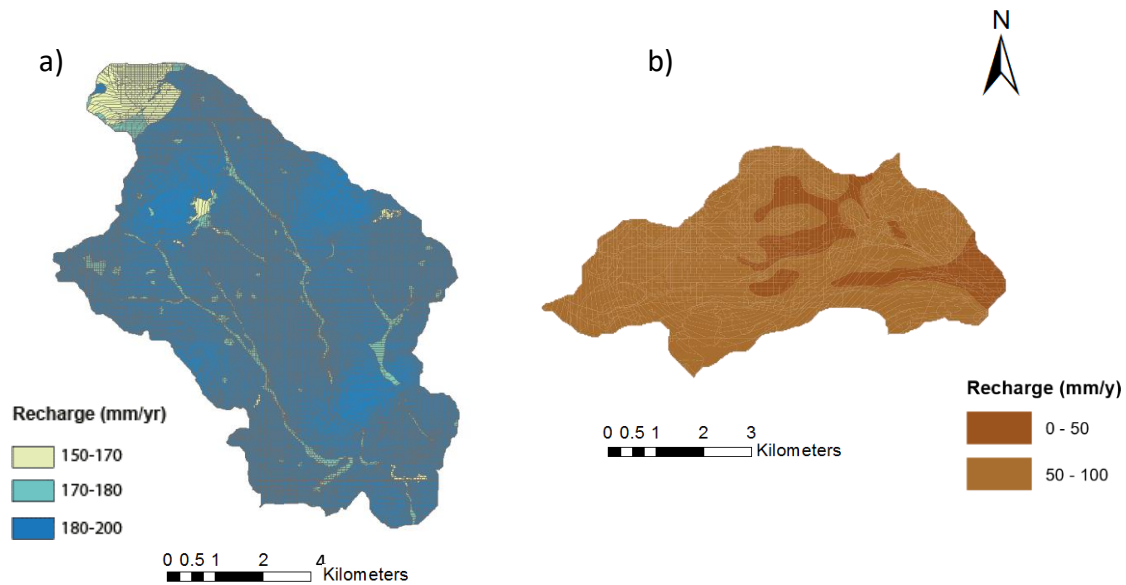


Figure 6.5: Recharge map obtained with the recharge coefficient approach of (a) the Dripsey catchment and (b) the Mattock catchment.

6.3.2. Water Table Fluctuation

As a part of the groundwater table fluctuation method, a lagged cross-correlation was calculated for all the monitoring points to determine the response time between rainfall events and water table rises (Table 6.1). In the Dripsey, contrasting response times and correlations were found. The results obtained for the DR1 cluster and the DR2 Deep monitoring point presented low correlation values and slow response times between 13 and 35h, suggesting a slow infiltration through the unsaturated zone. In contrast, the DR3 cluster and the DR2 Shallow borehole showed higher correlations and response times of just a few hours (1-7h). The prompt rise in the water table of the DR3 cluster is caused, in the case of the DR3-subsoil, by the limited depth of the monitoring point. In the case of the DR3-shallow, upward gradients are detected in this area (CDM and OCM 2010b) that could generate interferences with the signal (see Figure 3.6).

Overall, the borehole logs show shallow water strikes (4-5.5 mbgl) in the observation points with a faster response, while other monitoring points also present water strikes but deeper (9.75 to 15.2 mbgl), which highlights the importance of fractures as preferential pathways.

Table 6.1: Water table response times to rainfall events for each monitoring point.

Response time (h)			
Dripsey		Mattock	
DR1-Shallow2	13	MK1 Subsoil	6
DR1-Shallow	35	MK1 Shallow	13
DR1-Deep	28	MK1 Deep	-2
DR2-Shallow	7	MK2 Deep	-4
DR2-Deep	32	MK3 Subsoil	2
DR3-Subsoil	1	MK3 Shallow	4
DR3-Shallow	3		

The overall correlations obtained at the Mattock are low, comparable to the values obtained for the deep monitoring points at the Dripsey (Figure 6.6). Nevertheless, the Mattock presents rapid response times for all the monitoring points analysed. The response times show how the Shallow bedrock response is slow in comparison with the subsoil.

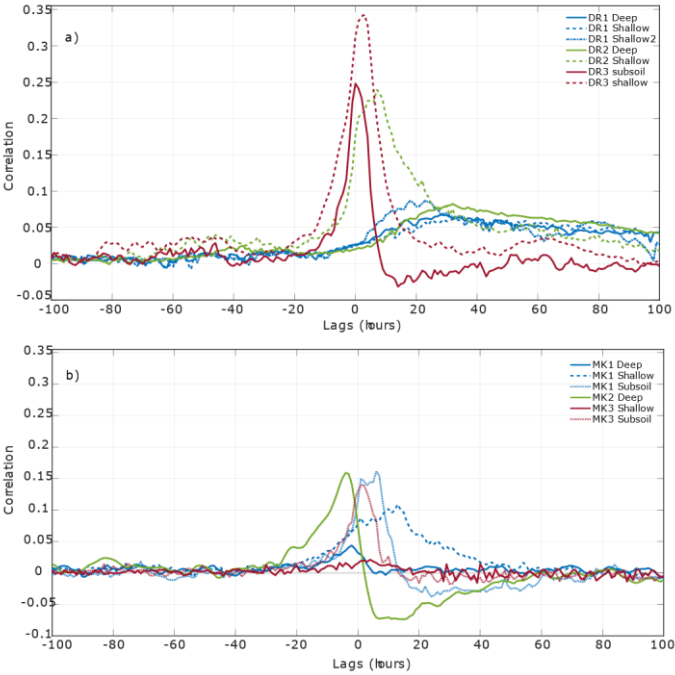


Figure 6.6: Lagged-Correlation between rainfall and water table rise for the Dripsey a), and the Mattock b).

However, the times in MK3 are significantly shorter when compared to the MK1: the response of the MK1 corresponds to the slow infiltration through the tills towards the

bedrock in a hillslope, whereas the MK3 cluster is located on the river plain and is influenced by shallower perched aquifers (see Figure 3.3). Moreover, it should be noted that the MK2-Deep borehole presents a negative time lag, which suggests that the rise of the groundwater level occurs before the rainfall event. This anomaly could be caused by a deep lateral flow intersected by this monitoring point. Hence, the negative values for the MK2-Deep borehole suggest that the system is independent of the rainfall events that it is being compared to, and therefore that the water levels may be responding to a deep groundwater flow from a different recharge area.

To complement the cross-correlation, a simple auto-correlation analysis was applied to all groundwater time-series to assess how the previous state of the water table controls the groundwater level dynamics. In the Dripsey catchment, a strong linear dependence is shown in all the series by smooth slopes with coefficients higher than 0.9 after 100 h lag. These small variations are not significant and cannot be translated into further physical interpretations of the system (Figure 6.7a). A similar behaviour is observed at the Mattock for the deep bedrock monitoring points (Figure 6.7b). Nevertheless, the MK1-shallow, MK1-subsoil and MK3-subsoil present steeper slopes, suggesting that this dependency increases with depth. Furthermore, the curves of the MK3 cluster are smoother than the equivalents in MK1 pointing to a larger linear dependency. These results would confirm that the MK3 observation points are linked to the shallower groundwater table (perched aquifers) and to the river which, in turn, is translated into a higher autocorrelation. Therefore, this would also be consistent with the response times calculated through the cross-correlation and supports the conceptual model of the catchment.

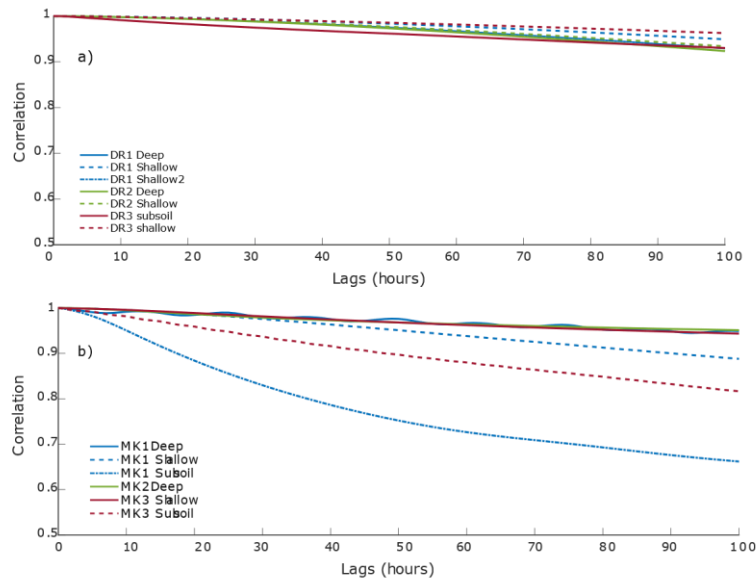


Figure 6.7: Autocorrelation of the groundwater level changes at each borehole a) For the Dripsey catchment and b) for the Mattock catchment

Figure 6.8.a shows the monthly recharge values calculated for the DR1-Shallow borehole. At first sight, the results appear to be inconsistent since the same amount of rainfall generates uneven recharge responses for different months. To understand this pattern, the recharge calculations must be compared with the water table levels, and the response of the water table to different rainfall inputs be analysed. Firstly, the largest recharge events can be linked to the times when the water table level rises by several metres after a long recession (e.g.: summer 2010, autumn 2014). Secondly, the months in which the recharge is lower than expected - or non-existent - correspond to high water table levels with “ragged” aspects such as winter 2012-2013 similarly to those described in Tedd et al.,(2012). This indicates that the aquifer is full when the water table reaches 190 mOD and cannot accept more groundwater recharge.

The results obtained at Mattock show a comparable behaviour (Figure 6.8.b), even though there are some minor differences due to the contrasting characteristics of the two catchments. In this case, when the estimated recharge is lower than expected, it can be mostly related to recession periods, where more than one month of abundant rainfall is needed for the levels to recover. In a couple of months (winter 2014-2015) the accumulated rainfall is very high, and the recharge generated lower than expected. These events are linked to high water table levels and not to a recession period as described before, so it could

be indicating that the aquifer is unable to accept further recharge i.e. that the recharge cap has been reached.

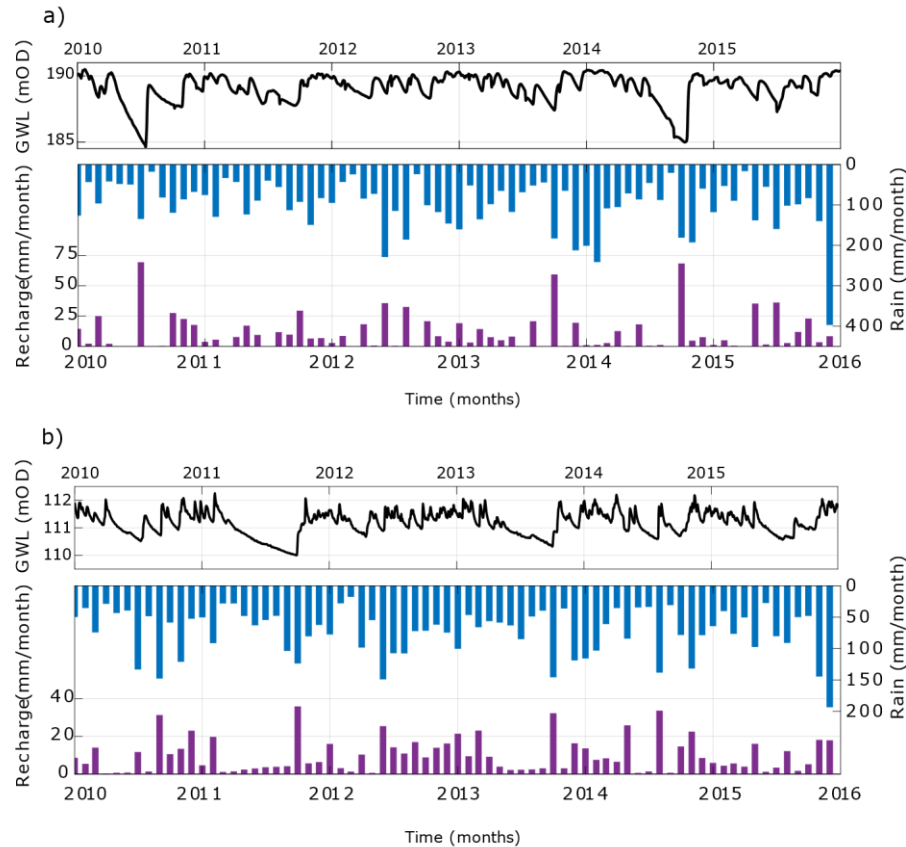


Figure 6.8: Observed groundwater levels and accumulated monthly rainfall (blue, right Y axis) and calculated monthly recharge (purple, left Y axis) for (a) the DR1-Shallow monitoring point and a S_y of 0.02 (Dripsey catchment) and (b) the MK1-Shallow and borehole, with a S_y of 0.02 (Mattock catchment).

Finally, the monthly estimations are aggregated in yearly values as shown in Table 6.2. Due to the uncertainty of the specific yield value, all the recharge estimations have been calculated with four likely S_y values using guidelines in Kelly et al., (2015), where it was concluded that PPAs generally have S_y values under 0.05.

The recharge estimates obtained for the Dripsey catchment show two anomalies that must be taken into consideration: firstly, groundwater recharge estimates are higher in the deeper boreholes than in the shallower, suggesting that there is an upward gradient from the deep to shallow, which is also described in the EPA report (CDM and OCM 2010b). Secondly, the results obtained for the DR2 cluster of boreholes present unusually high recharge values in comparison with the other boreholes. This could be due to the presence of water bearing

fractures, as there are several water strikes reported at all depths for the DR2 boreholes, including two low flow water strikes encountered in the open hole section of the DR2-Deep borehole, with an estimated discharge of 1.5 l/m. Alternatively, these exceptionally high values could instead be attributed to a locally lower S_y . Because of these anomalous values, the results obtained in the DR2 cluster of boreholes are not considered in the results interpretation below.

The estimates obtained for the Dripsey when applying a S_y of 0.01 and 0.02 give recharge estimates under 200 mm/y, which seem to underestimate recharge in the area when compared to the recharge coefficient approach (Section 6.3.1). Similar calculations performed by Tedd et al. (2012) for Locally important aquifers in Devonian Old Red Sandstones lead to a S_y range of 0.03-0.04. Hence, the recharge values obtained for these higher specific yield values are considered the most appropriate and have been used to interpret the results.

Similarly to the Dripsey, the results obtained for the Mattock by considering a S_y of 0.01 seem to underestimate recharge in the area when compared to the recharge coefficient approach and previous studies of the catchment. On the other hand, the computations using a specific yield of 0.03 seem to overestimate groundwater recharge as the values go up to 206 mm for the subsoil borehole at MK1. Furthermore the geometric mean of S_y of PPAs in Ireland is estimated as 0.017 (Kelly et al. 2015). Therefore, the recharge estimations calculated with a S_y of 0.02 are considered the most realistic and have been used to interpret the results.

Table 6.2: Annual average recharge estimated for each monitoring point and Sy. The shaded values (light orange) indicate the anomalous values obtained from the DR2 cluster of boreholes.

Dripsey					
	<i>Specific Yield</i>				
	0.01	0.02	0.03	0.04	0.05
	Recharge (mm/y)				
DR1-Shallow2	68	137	205	274	342
DR1-Shallow	64	127	191	255	318
DR1- Deep	80	160	240	320	399
DR2-Shallow	149	299	448	598	747
DR2-Deep	177	353	530	706	883
DR3-Subsoil	75	151	226	301	377
DR3-Shallow	47	94	141	189	236
Mattock					
	<i>Specific Yield</i>				
	0.01	0.02	0.03	0.04	0.05
	Recharge (mm/y)				
MK1-Subsoil	62	123	185	247	308
MK1-Shallow	59	118	177	236	295
MK1-Deep	45	90	135	182	228
MK2-Deep	35	67	101	130	162
MK3-Subsoil	48	96	144	192	240
MK3-Shallow	69	139	208	277	347

Detailed results of the yearly recharge estimations for each borehole are provided in Appendix A. A comparison of the annual recharge estimation with Figure 6.8 reveals that, in most cases, years such as 2010 and 2014, where there were relatively prolonged recession periods followed by important recharge events, often present higher recharge values than years such as 2011 to 2013 where the aquifer never entered a significant recession and, even though there were some important rainfall events, the aquifer is full through all the seasons and unable to accept this potential recharge. Thus, these results provide evidence of the effect of rainfall seasonality on groundwater recharge and suggest that the acceptance capacity of these aquifers is state (and time) dependent.

6.3.3. Baseflow separation

The Eckhardt recursive digital filter was applied to the discharge time series over the 2012-2015 period to determine the proportion of streamflow stemming from groundwater in the study catchments. Firstly, the α parameter (Eq. 6.6) was assessed by applying the 5-day recession analysis and fitting a linear trend to the scatterplot (Figure 6.9) as well as the corresponding values to the 95 % confidence interval as described in (Eckhardt 2005).

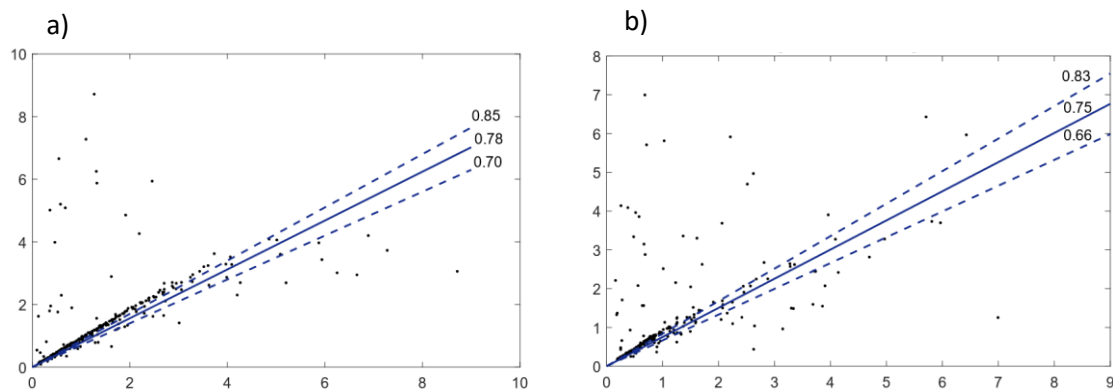


Figure 6.9: Scatter plot of the discharge in recession periods of 5 days or longer with the corresponding fitted linear trend (solid blue) and its 95% confidence interval (dashed blue) for a) the Dripsey, and b) the Mattock.

The three α values were used to assess the baseflow (Table 6.3) while fixing the BFI_{max} value to the default value for fractured aquifers. The range of BFI obtained for the Dripsey is narrow, varying from 32 to 36%, corresponding to recharge estimations from 210 to 258 mm per year. Similarly, the BFI obtained for the Mattock is in the range of 31 to 35% with equivalent values of 209 to 255 mm per annum. In both cases, the variation of the recession parameter causes less than 50 mm variation in the annual recharge, so the central value has been adopted here. These results suggest that the two study areas present similar annual recharge, which is not consistent with previous studies of the two areas, and appear particularly high for the Mattock compared with the currently accepted recharge cap of 100 mm/y.

Table 6.3: Estimated baseflow and baseflow indices for the three considered recession parameters over the study period.

Dripsey						
	α_{70}		α_{78}		α_{85}	
	Base Flow	BFI	Base Flow	BFI	Base Flow	BFI
2012	211	0,32	210	0,32	207	0,33
2013	210	0,33	209	0,34	208	0,35
2014	255	0,33	256	0,34	258	0,36
2015	239	0,32	236	0,32	231	0,33
Mattock						
	α_{66}		α_{75}		α_{84}	
	Base Flow	BFI	Base Flow	BFI	Base Flow	BFI
2012	212	0,32	211	0,32	209	0,33
2013	211	0,32	210	0,33	209	0,35
2014	252	0,33	253	0,34	255	0,35
2015	246	0,31	243	0,32	237	0,33

Given the impossibility of calculating the BFI_{max} term (Eckhardt 2005, 2012), the default value for fractured aquifers was used (0.25) together with two other likely values (0.20, 0.30), and the resulting baseflow estimations were compared to the water table levels observations, as presented in Figure 6.10. It shows that the baseflow estimations can reproduce the oscillations and trends of the observed groundwater levels. It can also be observed that, unlike the parameters of other baseflow separation methods, the variation of BFI_{max} does not affect the shape of the simulated baseflow but has a sharpening/smoothing effect.

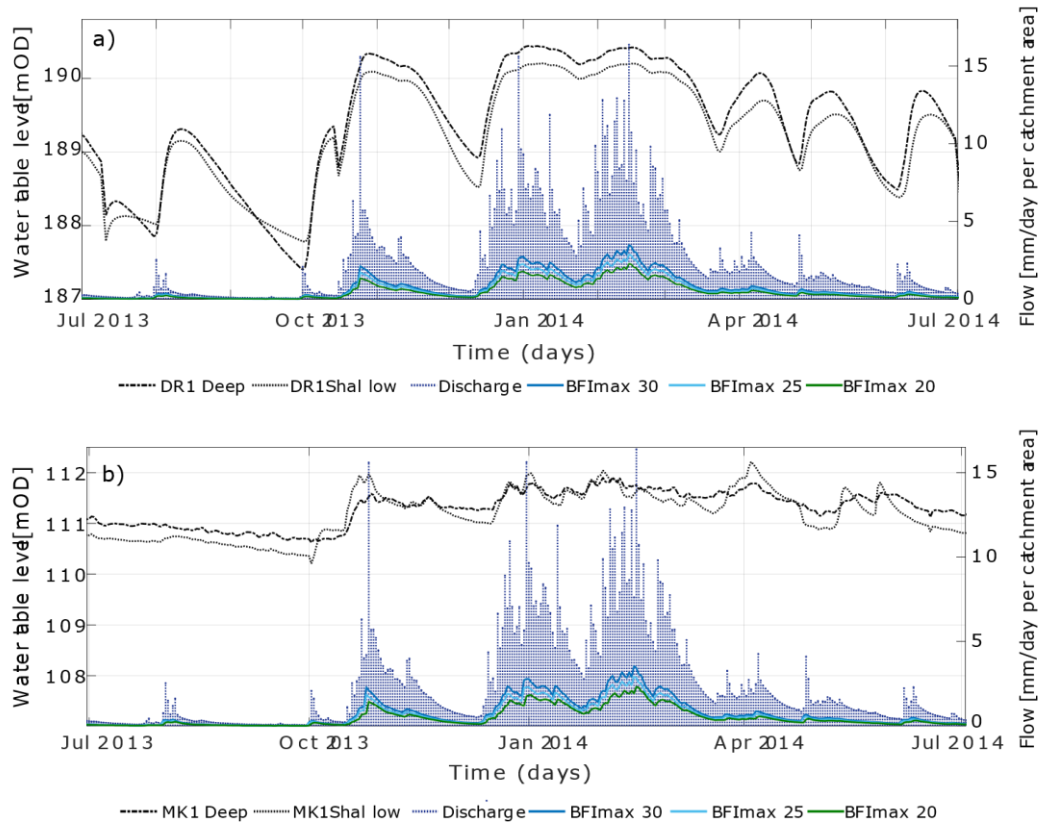


Figure 6.10: Comparison of groundwater levels (black lines) at different monitoring points, observed discharge time series (dark blue area), and estimated baseflow for different BFI_{max} parameters over the study period for a) the Dripsey and b) the Mattock catchments.

Even though the Dripsey catchment has been studied previously for nutrient transport purposes and from a flooding point of view (e.g. Jordan et al. 2005; Kiely et al. 2008), it has received little attention from the hydrogeological point of view. For this reason, there are no available previous studies to compare the results obtained with the Eckhardt filter (Table 6.4). Nevertheless, with the results obtained by the other methods, and the general knowledge of the Dripsey catchment it seems reasonable to consider as valid the results obtained with the BFI_{max} value of 30, which would correspond to BFI of 32-34% and annual recharge values from 209-256 mm/year.

Table 6.4: Annual baseflow estimation (mm/y) and corresponding baseflow index (BFI) (%) estimated from the evaluation of the BFI_{max} parameter for the two study catchments.

Dripsey							Mattock					
	BFI_{max} 20		BFI_{max} 25		BFI_{max} 30		BFI_{max} 20		BFI_{max} 25		BFI_{max} 30	
	BF	BFI	BF	BFI	BF	BFI	BF	BFI	BF	BFI	BF	BFI
2012	139	0.22	174	0.27	210	0.32	139	0.22	176	0.27	211	0.32
2013	139	0.23	174	0.28	209	0.34	139	0.22	175	0.28	210	0.33
2014	171	0.24	213	0.29	256	0.34	170	0.23	211	0.29	253	0.34
2015	156	0.22	196	0.27	236	0.32	157	0.21	201	0.27	243	0.32

Unlike the Dripsey, the Mattock catchment has been studied in detail from the hydrogeological point of view, and other baseflow separation methods have been applied in other research projects. O'Brien, et al. (2013) modified the Lyne & Hollick algorithm to separate the hydrograph in the different flow components. The overall groundwater contribution to the streamflow was estimated to be 23%. The Pathways report (Archbold et al., 2013) calculated the groundwater contribution by using chemical separation methods for different flow states. The results show that the contributions during January and February of 2012 were of 27% and 20% during the month of June. These baseflow estimations indicate that the best BFI_{max} value of those used above is 0.20 and hence that the BFI for the Mattock is 21-23% and the recharge of 140-170 mm/y.

6.3.4. NAM rainfall-runoff modelling

The NAM conceptual rainfall-runoff model was applied to the two study catchments in order to provide further recharge estimations for these areas. The meteorological and hydrological data presented in Sections 3.2.2 and 3.2.3 were used to calibrate the model for both catchments.

In the case of the Dripsey catchment, the available time-series were divided into a calibration period (2012-2014) and a validation year (2015) as shown in Figure 6.11a. The calibration of the Dripsey catchment led to good performances, with a KGE score of 0.86 and an NSE of 0.79, and the same R^2 value (0.79). The performances during the validation period were quite similar with a KGE of 0.82, NSE of 0.85 and R^2 of 0.86. Additionally, the overall error in water balance was also calculated. The results suggest that the simulated flows overestimate river

discharge by 1.84% over the calibration and validation periods, which corresponds to a total error of 58 mm approximately.

In contrast, the calibration of the NAM for the Mattock catchment involved more complications. Given the small area of the catchment and its complexity, it was not possible to achieve a good enough calibration based on the data from Dunsany rainfall station at hourly resolution. For this reason, additional meteorological and hydrological data provided by the EPA (which was part of the Pathways project and a previous doctoral dissertation) was used to calibrate the NAM for the Mattock catchment (see Section 3.2.2). This data, however, is only available for a short period of time, so it has all been used in the calibration of the model, given the need for it to capture different flow regimes, and no validation was performed.

The performance achieved for the Mattock was lower in comparison with the Dripsey with a KGE of 0.72, NSE value of 0.54 and R^2 of 0.56. In this case the error in the simulated discharge volume over the calibration period is 1.3% higher than observed which corresponds to an error of 77 mm approximately (Figure 6.11b).

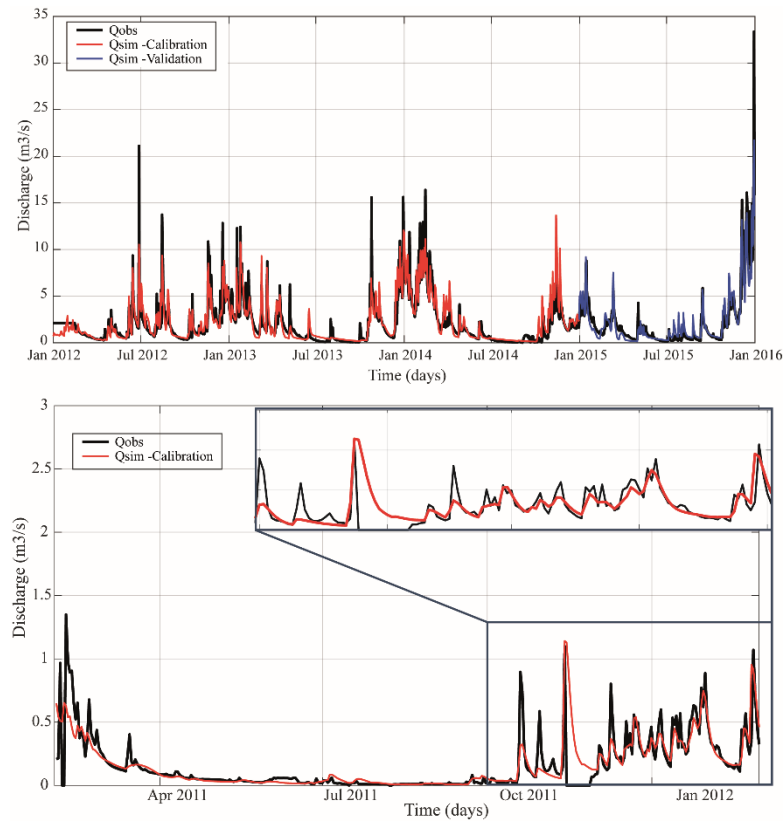


Figure 6.11: Comparison of observed vs simulated discharge during the calibration and validation period for a) the Dripsey and b) the Mattock.

As can be observed in Figure 6.11, the proportion of the available data used for calibration of the Dripsey is significantly longer than the proportion used for validation, which was not possible to perform for the Mattock as mentioned above-. This division strategy aims to capture a wide range of hydrological regimes in which the model is calibrated to maximize the transferability of the model, as it is later applied using future climate projections (see Chapter 9).

The NAM model was also used to identify the contribution of the different pathways to the resulting hydrograph, as presented in Table 6.5. The results suggest that the Dripsey catchment is dominated by interflow (35%) and overland flow (33%) which together account for almost 70% of the flow. Thus, groundwater contribution is around 31%, with a clearly predominating shallow groundwater contribution (24.8%). This baseflow index corresponds to groundwater recharge values ranging from 220-262 mm/y over the calibration and validation period, with an average of 240 mm/y.

In the case of the Mattock, interflow was observed to be the predominant pathway accounting for 41% of the flow, followed by the overland flow (40.9 %), which most probably gains relevance during rainfall events given the *flashy* nature of the catchment. Consequently, just about 17.4% of the flow stems from groundwater contribution. This percentage would correspond to a groundwater recharge of 61 mm over the year used in the calibration process. However, if this percentage is applied to the observed discharge time-series over the 2012-2015 period, the recharge values obtained range between 78-91 mm/y, with an average of 83 mm/y. These values are consistent with those calculated by O'Brien et al., (2013a) which estimated the baseflow by 16.9% at Berril's Farm with a 9.9 % contribution from the Deep groundwater reservoir and 6.8 from the shallow groundwater. Interflow was estimated by 45.7 % and overland flow by 37.6%.

Table 6.5: Results of the NAM modelling after calibration, with contribution (%) of each flow component.

	Mattock	Dripsey
Overland Flow (%)	40.9	33.3
Interflow (%)	41.6	35.2
Shallow Groundwater (%)	10.3	24.8
Deep Groundwater (%)	7.1	6.5
Total Baseflow (%)	17.4	31.3

6.3.5. Dupuit-Forchheimer Calculations

The groundwater level data have been combined with the hydraulic conductivity estimations -presented in the EPA report on the catchments (CDM and OCM 2010a, b) - to estimate recharge using an adaptation of the Dupuit-Forchheimer equation (Section 6.2.5).

The hydraulic conductivities obtained from EPA were estimated from pumping tests for each cluster of boreholes, at different depths present at the reports (CDM and OCM 2010b, a). Table 6.6 shows the values obtained, which present a wide range of up to three orders of magnitude for the Dripsey, and two for the Mattock. Such a range of the aquifer's hydraulic properties corresponds to the characteristic heterogeneity and anisotropy of fractured bedrock aquifers (see Section 2.2).

Table 6.6: Hydraulic conductivity estimation for each monitoring point (Source: CDM and OCM 2010a, b)

Dripsey		Mattock	
<i>Monitoring point</i>	<i>K (m/d)</i>	<i>Monitoring point</i>	<i>K (m/d)</i>
DR1-Shallow	2.53E-03	MK1-Shallow	7.68E-04
DR1-Deep	2.30E-04	MK1-Deep	7.29E-04
DR2-Shallow	2.84E-02	MK2-Shallow	2.81E-04
DR2-Transition Zone	1.79E-01	MK2-Shallow	1.38E-04
DR2-Deep	4.70E-03	MK2-Deep	1.75E-03
DR2-Deep	5.22E-04	MK2-Deep	4.33E-04
DR3-Shallow	8.20E-02	MK3-Shallow	3.16E-04
DR3-Deep	1.71E-01	MK3-Deep	1.14E-02
DR3-Deep	9.76E-03	MK3-Deep	1.22E-02
		MK3-Deep	3.00E-03

A total of 8 tests were conducted for the Dripsey catchment (excluding the test performed in the Transition Zone), which resulted in an average hydraulic conductivity of 0.03 m/d and a corresponding geometric mean of 0.007 m/d. In the case of the Mattock, 10 tests were performed resulting in an average hydraulic conductivity of 5.9×10^{-4} m/d and an equivalent geometric mean of 0.003 m/d. However, it should be borne in mind that the EPA report highlights that the conductivity values at the MK2-Shallow and MK2-Deep boreholes could be higher as the rising head tests at MK2-Deep captured just the very late phase of the water table recovery, and water was added during the falling head test in MK2-shallow as the well was dry during October 2008. For this reason, these values have been omitted from the means used to approximate groundwater recharge as they would lead to what would be considered to be unrealistically low values. Hence, an average of 0.0047 m/d and a corresponding geometric mean of 0.0076 m/d have been used for the Mattock catchment. In order to reduce the effect of the extreme values, the hydraulic conductivity values used in the calculations are those obtained by the geometric means in both catchments.

Groundwater recharge was calculated by using the monthly averages of the water table elevation, that were then aggregated into yearly estimations. The results obtained for the Dripsey suggest a recharge range from 269-287 mm/y and 169-172 mm/y for the Mattock (Table 6.7). For comparison, groundwater recharge was also estimated using the annual

average groundwater levels of each borehole leading to recharge values of 278 mm/y and 172mm/y for the Dripsey and the Mattock, respectively.

Table 6.7: Annual recharge estimations from Dupuit-Forchheimer calculations

	DR-Recharge (mm/y)	MK-Recharge (mm/y)
2010	269	172
2011	281	169
2012	282	170
2013	287	169
2014	276	169
2015	283	168
Average	278	172

6.3.5.1. Transmissivity and Conductivity Estimations

The data of the pumping and recovery tests summarized in the EPA report on PPAs has been used to approximate the aquifer the transmissivity and conductivity in the Dripsey (DR3-Deep) and Mattock (MK3-Deep) through the application of the Cooper-Jacob solution (Figure 6.12).

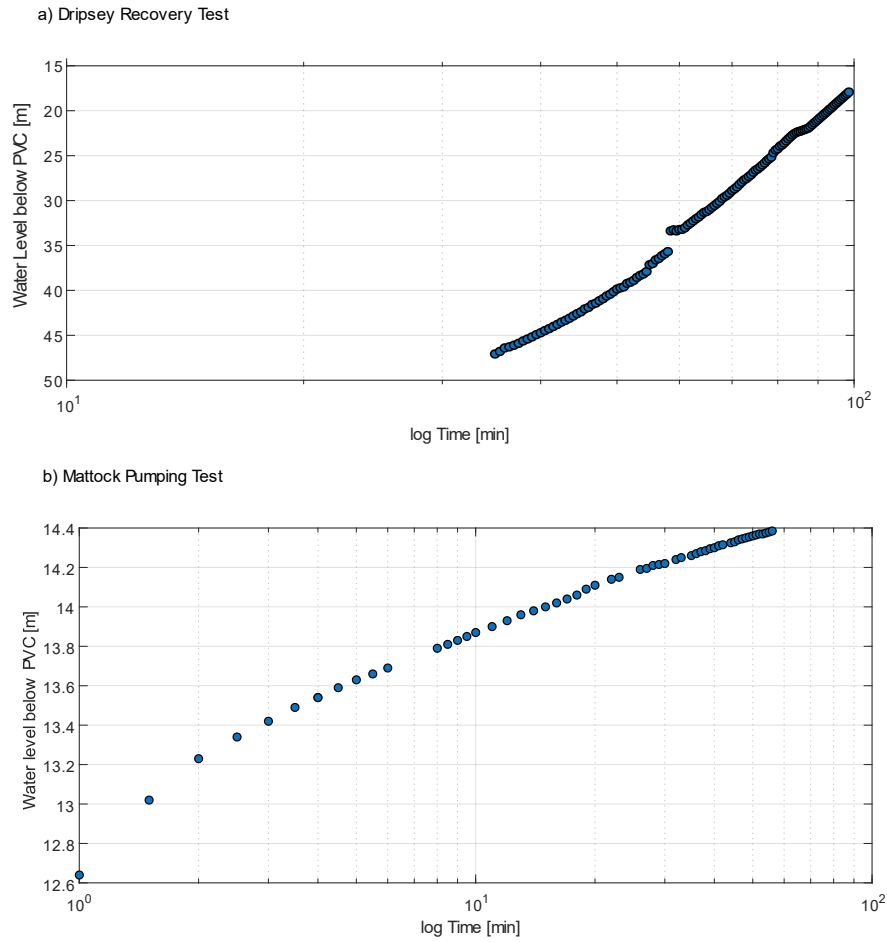


Figure 6.12: a) Recovery test for the DR3-Deep monitoring point and b) Pumping test for the MK3-Deep borehole.

By applying Eq.6.9 presented in Section 6.2.6, and with the known data of the sites and tests conducted (CDM and OCM 2010a, b) transmissivity values of $3.4 \text{ m}^2/\text{d}$ are obtained for the Dripsey (Eq.19) and $8.7 \text{ m}^2/\text{d}$ for the Mattock (Equation 20):

$$T = \frac{2.30 \cdot 8.46}{4\pi \cdot 0.21} = 7.2 \text{ m}^2/\text{d} \quad (6.19)$$

$$T = \frac{2.30 \cdot 36}{4\pi \cdot 0.76} = 8.7 \text{ m}^2/\text{d} \quad (6.20)$$

These results are consistent with the data published in the Geological Survey of Ireland manual and database of aquifer properties (Kelly et al. 2015), where it is indicated that the transmissivity for PPAs is typically less than $10 \text{ m}^2/\text{d}$. Additionally, they propose best transmissivity estimates of $5 \text{ m}^2/\text{d}$ for both Old Red Sandstone (Dripsey), and Ordovician

Metasediments (Mattock). The corresponding upper values are 75m²/d and 46 m²/d (90th percentile), whereas the lower values are 1m²/d and 0.5m²/d (10th percentile).

Furthermore, if the thickness of the aquifer (b) is assumed to be 100 m, then the hydraulic conductivity (K) can be calculated from the estimated transmissivity (T) according to Eq.6.21:

$$K = \frac{T}{b} \quad (6.21)$$

$$T = \frac{7.2}{100} = 7.2 * 10 \text{ m/d} \quad (6.22)$$

$$T = \frac{8.7}{100} = 8.7 * 10 \text{ m/d} \quad (6.23)$$

which provides K values in consistent with those presented in Table 6.7.

6.3.6. Recharge estimations summary

Table 6.8 summarises the recharge estimations obtained by applying the five methods presented above. The water table fluctuation method is the approach giving the largest variations in the recharge estimations. This is to be expected, as this approach is affected by the variability of hydraulic properties from borehole to borehole, in addition to the interannual variability that affects all the methods. Moreover, even though the clusters of boreholes are separated by just a few tens of metres the properties of the bedrock change rapidly and it reflects on the annual estimations (see Appendix A). Hence, the representation of the results as a single average value is an important simplification of the outcomes used solely for comparison purposes.

Overall, the recharge coefficients approach is the method resulting in the lowest recharge estimation. However, it must be taken into account that this method was conceived to assess the groundwater resources that are available for long-term and sustainable abstraction (Hunter Williams et al. 2013). Therefore, this approach neglects groundwater resources with short residence time such as those present in the subsoil or transition zone. Consequently, to have a suitable comparison, the results should be contrasted with the recharge estimations computed for the shallow and deep bedrock boreholes.

Finally, the baseflow separation and the NAM present similar results for the Dripsey, with average annual recharge values between 227 and 240 mm/y. The use of baseflow as a proxy for groundwater recharge is, in fact, estimating net recharge - lateral contributions to other aquifers and abstractions are not considered – and so it can underestimate significantly groundwater recharge. Therefore, it is reasonable to assume that average groundwater recharge in the Dripsey catchment is at least 240 mm/y. Hence, groundwater recharge in the range of 200 to 300 mm/y would be plausible according to the results obtained.

In the case of the Mattock, the results are disparate, as the result obtained for the baseflow separation was almost twice the outcome of the NAM. This dissimilarity is likely to be due to the uncertainties associated with each method stemming from the inability of computing BFI_{max} for the Eckhardt filter, and the difficulties for calibrating the NAM. Considering the results obtained by other methods and from previous studies on the catchment, the most likely recharge estimates would range between 90-150 mm/y, even though plausible recharge estimates could range from 70 to 170 mm/y approximately.

Table 6.8: Range of recharge values obtained for each calculation method.

Dripsey			
	Minimum	Maximum	Average
	(mm/y)	(mm/y)	(mm/y)
Recharge coefficients	-	-	200
Water Table Fluctuation	141	320	232
Baseflow Separation	209	256	227
NAM	220	262	240
Dupuit-Forchheimer	269	287	278
Mattock			
	Minimum	Maximum	Average
	(mm/y)	(mm/y)	(mm/y)
Recharge coefficients	-	-	100
Water Table Fluctuation	67	177	149
Baseflow Separation	139	170	151
NAM	78	91	83
Dupuit-Forchheimer	168	172	172

6.3.7. Specific yield estimations from Water Table Fluctuation: Inverse modelling

The range of annual recharge values obtained by applying the set of recharge calculation methods presented in Table 6.8 has been used to estimate an “*effective*” S_y value for the catchment by inverting equation (1). Given the results obtained, the S_y for the Dripsey has been evaluated based on a range of recharge between 200 mm/y and 300 mm/y, and 50 mm/y to 170mm/y for the Mattock.

Table 6.9 presents the results obtained for each monitoring point and equivalent annual recharge. These values are the geometrical mean of the four years period for which these calculations have been carried out (2012-2015). It also presents a generalised S_y estimation, which is the geometric mean of the previous approximations. The specific yield estimations for the Dripsey catchment range from 0.029 for an equivalent recharge of 200 mm/y to 0.044 for annual recharge values of 300 mm/y. The S_y values calculated for the Mattock present a slightly larger variability with S_y values ranging from 0.015 to 0.04 for an equivalent annual recharge of 70 mm/y and 170 mm/y, respectively. The variability observed between the different boreholes highlights how rapidly the hydraulic variables can change in fractured bedrock aquifers, even within few metres.

Table 6.9: S_y estimations from equivalent annual groundwater recharge.

Dripsey			
	Recharge 200 mm/y	Recharge 250 mm/y	Recharge 300 mm/y
<i>Monitoring point</i>	<i>Specific Yield Estimation</i>		
DR1-Shallow	0.03	0.04	0.05
DR1-Shallow2	0.03	0.03	0.05
DR1-Deep	0.04	0.03	0.05
DR2-Shallow	0.01	0.02	0.02
DR2-Deep	0.03	0.02	0.04
DR3-Shallow	0.04	0.05	0.06
Geometric Mean	0.029	0.030	0.044

Mattock			
	Recharge 70 mm/y	Recharge 100 mm/y	Recharge 170 mm/y
<i>Monitoring point</i>	<i>Specific Yield Estimation</i>		
MK1-Subsoil	0.012	0.02	0.03
MK1-Shallow	0.012	0.02	0.03
MK1-Deep	0.016	0.02	0.04
MK2-Deep	0.022	0.03	0.05
MK3-Subsoil	0.015	0.02	0.04
Geometric Mean	0.15	0.02	0.04

6.4. Discussion and conclusion

As a first approach to assess the possible impacts of climate change in Ireland, a sensitivity analysis was carried out to examine the control exerted by the meteorological and hydrogeological variables (see Chapter 4). The results showed that the hydrogeological settings – and especially the aquifer storage capacity - have a larger control on local recharge than the meteorological factors. In the Irish context, this storage capacity has been typically approximated by recharge caps for those aquifers regarded as poorly productive (Hunter Williams et al., 2013). Here, a recharge characterisation has been conducted in order to assess the recharge acceptance of these aquifers by constraining the recharge uncertainty. Then, the recharge estimations have been used to assess the specific yield.

The water table fluctuation method complemented with the cross correlation and autocorrelation procedures (Cai and Ofterdinger 2016) have provided useful information on the catchments. For instance, the aquifers' response times assessed through lagged cross correlation illustrated the intrinsic heterogeneity of these fractured aquifers while also highlighting the role of fractures as preferential infiltration pathways. Overall, the autocorrelation and the cross correlation are especially useful to complement and/or confirm catchment conceptual models, as some recharge mechanisms can be inferred from these techniques as Lee and Lee (2000) suggested.

Furthermore, the results obtained with the water table fluctuation approach have demonstrated the limited storage capacity of the aquifers underlying the study areas. Moreover, the effect of rainfall seasonality on annual groundwater recharge becomes apparent when these results are analysed year per year: it was shown that the years with dry summers, which are followed by wet winters, gave a larger groundwater recharge than wetter years in which aquifers did not enter in recession (which would match an intuitive understanding of the process). Hence, in the years with a more acute rainfall seasonality, the annual recharge values are more likely to surpass the established recharge caps, even in the shallow and deep bedrock boreholes. Nevertheless, the main implication is that the aquifer recharge acceptance capacity depends on the aquifer state and hence that expressing the storage capacity as a unique annual recharge value could lead to a significant underestimation of the groundwater resources. To be able to provide a more accurate estimation it would be necessary to have a continuing knowledge of the aquifer state (water table level and recharge in the previous months), which is not feasible at present in most of catchments in Ireland.

The combination of groundwater recharge calculation methods has provided a range of likely annual recharge for each study area. In the case of the Dripsey, this ranges from approximately 200 to 300 mm/y whereas the values obtained for the Mattock catchment vary from approximately 70 to 170 mm/y. Consequently, these calculations suggest that recharge caps could be underestimating annual groundwater recharge by up to 100 mm/y in the Dripsey and 70 mm/y in the Mattock.

These annual recharge values correspond to equivalent "effective" specific yield values between 0.029 and 0.044 for the Dripsey, and 0.015 and 0.3 for the Mattock. These results are consistent with the values calculated by Tedd et al. (2012) and the values reported in the

GSI database of aquifer properties (Kelly et al. 2015). This approach to assessing the specific yield differs notably from the more classical approach of pumping and recovery tests analysis and/or inverse modelling. Nevertheless, the recharge estimations carried out through the water table fluctuation (Section 6.3.2), but especially the variability in the hydraulic conductivity estimations (6.3.5), highlight the heterogeneity characteristic of fractured bedrock aquifers and demonstrate how hydraulic properties can change rapidly within short distances. Because this research is set within a framework of climate change impact assessment, it has been considered more appropriate to estimate “*effective*” parameters over the catchments rather than site-specific estimations. Even though this method has been conceived as a way to have a practical first estimation of the specific yield within an area it has been proven effective as the S_y values obtained are consistent with previous studies.

7. Linking Irish Climate Variability and Groundwater Level Dynamics

7.1. Introduction

The Sensitivity Analysis presented in Chapter 4 has shown that the hydrogeological properties have a larger effect on the long-term groundwater recharge than the changes in precipitation intensity or seasonality, when the total precipitation amounts are preserved. However, the results indicate a clear linear relationship between these changes in the precipitation patterns and the annual groundwater recharge. These results are consistent with those obtained for the soil moisture budget analysis (Chapter 5) that suggest that any enhancement in rainfall intensity or seasonality would lead to higher infiltration. In a similar vein, the outputs of the Water Table Fluctuation method indicate that years with a well-marked seasonality tend to have a higher annual recharge and are more likely to surpass the established recharge caps (see Section 6.3.2). In the context of this thesis, these changes have been framed as a possible effect of climate change. However, natural long-term climate variability can also lead to increased storminess or enhanced seasonality.

Large scale atmospheric and oceanic circulation patterns control the primary components of the hydrological cycle, which are rainfall and temperature. Therefore these patterns, or Teleconnection indices, also regulate the multiannual to multidecadal variability of other components of the hydrological cycle such as river discharge, snow accumulation and runoff, and groundwater recharge (Hanson et al. 2004, 2006; Gurdak et al. 2009; Holman et al. 2009, 2012). The climate variability induced by these telecommunication indices has been widely investigated world-wide, as well as its effects on streamflow (Ropelewski and Halpert 1987; Ghil et al. 2002; Ge and Gong 2009). However, the effects of the low-frequency climate variability on groundwater has been comparatively less studied and, consequently, their impacts on local groundwater recharge mechanisms are still largely unknown, including in Ireland.

Moreover, for the understanding of the interaction of these low-frequency climate variability modes with groundwater levels, it is of crucial importance for a better assessment of the local impacts of climate change, as several authors have found that the GCMs fail to fully

represent the large-scale climate features and/or their periodicities (Stephenson et al. 2006; Stoner et al. 2009; Furtado et al. 2011; Lapp et al. 2012).

Anthropogenic activities have altered the Earth's climate by modifying the extremes of rainfall, temperature, evaporation and streamflow, to the point that the stationarity of the hydrological processes can no longer be assumed (Milly et al. 2008). Therefore, as has been mentioned in previous chapters, an intensification of the hydrological cycle is expected as a consequence of climate change. Just in the last five years, exceptional events from both extremes have occurred in Ireland; with a particularly wet winter in 2015-2016 that caused flooding and groundwater flooding (McCarthy et al. 2016), and an exceptionally dry summer in 2018 which lead to a hydro(geo)logical drought (Falzoi et al. 2019).

However, given that the climate models are unable to fully represent these large-scale climate patterns, it is still unknown how these climate indices will interact with the anthropogenically induced processes, and the consequences that this could have on the long-term modifications of the hydrological cycle, as well as on the extreme events. Furthermore, stress on groundwater resources could be accentuated by indirect impacts such as population growth, and the consequent increase on food and water requirements (Taylor et al. 2013). Therefore, investigating the variations of the hydrological variables and their implications on water resources availability is becoming crucial (Massei et al. 2010), and a deep understanding of local recharge processes is required for a wiser and more sustainable water resources management.

In signal analysis terms, the changes in the means are reflected in the trends, whereas the modification of the frequency of occurrence of exceptional events is translated into changes in the frequencies or periods. The analysis of frequencies has been classically studied through Fourier-transform-based spectral analysis, which allows the determination of the frequency content of a signal or the evaluation of process-based models among other applications (Fleming et al. 2002). However this method presents strong limitations when applied to transient processes as is often the case in hydrological sciences (Labat 2005). To overcome this limitation, Wavelet Transforms (WT) methods have been developed in the last few decades and are widely used in geosciences in a range of applications, and provide an effective approach for hydrologic time series analysis (Kumar and Foufoula-Georgiou 1997; Saco and Kumar 2000; Veneziano et al. 2006). Continuous Wavelet Transforms (CWTs) have become a common tool in karst hydrology due to the high non-linearities that these

catchments present. For instance, CWTs have been used to perform time-frequency analysis of catchments (i.e. Chinarro et al. 2012; Hao et al. 2012), to determine the influence of North Atlantic Oscillation (NAO) on springs (Andreo et al. 2006) or investigate the impact of anthropogenic and climate pressures (Charlier et al. 2015).

Similarly, Wavelet Coherence (WTC) has also been extensively applied in geosciences and it is frequently used to analyse the effect of large-scale circulation patterns. For instance, Grinsted et al. (2004) examined the connection between the Atlantic Oscillation, and the Baltic Sea ice extent. This methodology has been successfully applied in a number of studies to investigate the relationship between teleconnection patterns and groundwater resources (e.g.: Holman et al. 2011; Tremblay et al. 2011; Perez-Valdivia et al. 2012; Kuss and Gurdak 2014; Lavers et al. 2015; Velasco et al. 2017; Neves et al. 2019) demonstrating not just that groundwater resources are affected by low-frequency climate variability, but also that the teleconnection patterns often explain a large proportion of the groundwater level variability.

The aim of this chapter is, on one hand, to explore the rainfall-recharge relationship for the study areas (see Figure 3.1) and, on the other hand, to assess the seasonal to multiannual influence of the teleconnection indices on the groundwater levels (GWL). To do so, Continuous Wavelet Transforms and Wavelet Coherence have been applied (as described in the following Section 7.2.1). Firstly, the infiltration and recharge processes are examined through the application of the wavelet coherence at daily resolution to analyse the short to mid-term rainfall-GWL dynamics. Secondly, the connection between the indices and the groundwater levels is investigated similarly with wavelet coherence at monthly time-steps to look into the seasonal to multiannual effect of these indices on the Irish groundwater resources.

7.2. Methods

In this section the methodology used to assess the relationship between climate variability and groundwater level dynamics is presented. Firstly, an overview of Wavelet Transforms analysis is described; this method has been used for both the analysis of the relationship between rainfall, temperature and groundwater levels, and in the assessment of the influence that large-scale atmospheric patterns exert on the groundwater resources. Secondly, the climate indices used in this assessment are described.

The groundwater levels in the Mattock (MK1-Shallow monitoring point) and the Dripsey (DR1-Shallow monitoring point) have been monitored for about a decade as the boreholes were installed on 2008 (see Section 3.2.2 and 3.2.3). Even though these time-series are long enough to examine the link between precipitation and groundwater, they are insufficient to fully capture the effect of the teleconnection patterns, which present multiannual - and up to multidecadal - periodicities. For this reason, an additional study site is analysed in this chapter: The Knocktopher (see Section 3.2.5). The Knocktopher borehole is located near the village of Knocktopher (Co. Kilkenny) and groundwater level records are available since 1980. However, the dataset presents some long and frequent discontinuities that couldn't be reconstructed by simple interpolation methods. Like the Dripsey, the Knocktopher borehole is installed in a Moderately Productive only in Local Zones aquifer (LI) with an associated recharge cap of 200mm/y (see Section 3.2.5). Hence, the two main study catchments (i.e. Mattock and Dripsey), and an additional borehole (Knocktopher) are used in this chapter (see Figure 3.1).

7.2.1. Wavelet Transforms

In hydrological and hydrogeological sciences, the processes are commonly represented by non-stationary time-series, which typically present trends, oscillations, abrupt changes and extreme values. These characteristics of the series are often the most interesting as they can provide valuable information on the system considered. These features have been often studied through Fourier Transforms, which are based on the principle that any periodic function can be decomposed to a sum of sine and cosine waves (Fourier 1822). However, these infinite sine and cosine waves are not localised in either time or space. Consequently, despite being able to establish all the frequencies contained in a signal, it is not possible to determine when these frequencies are occurring. This is one of the implications of Heisenberg's uncertainty principle (Heisenberg 1927). In signal analysis, this is known as the Gabor limit (or Heisenberg-Gabor limit), and it implies that it is not possible to determine the frequency and time of occurrence of a specific frequency in a signal (Gabor 1946).

In the last decades, several techniques have been developed in order to overcome Heisenberg's uncertainty principle - and to be able to represent signals as points in the time-frequency space - the most recent being wavelet transforms (Valens 1999). Wavelet transforms (WT) are powerful mathematical tools, mainly used to provide a full time-scale

representation of transient phenomena occurring at different time scales (Labat et al. 2000a). They can be defined as rapidly decaying wave-like oscillations with 0 mean (Valens 1999). These oscillations are based on mathematical functions called mother wavelets that can be translated through the signal (*shifting*) and compacted or elongated (*scaling*) to achieve a complete representation of the signal:

$$\Psi_{s,\tau}(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t - \tau}{s}\right) \quad (7.1)$$

where Ψ is the mother wavelet, s is the scaling factor, τ is the translation factor and t represent time. These wavelets must comply with strict mathematical conditions called “admissibility conditions”, as summarized in Labat et al. (2000), which ensure that the wavelet functions fulfil their characteristics of presenting a 0 mean (Eq. 7.2), and being localised in both time and frequency space (Eq 7.3).

$$\Psi_{s,\tau}(t) = \int_{-\infty}^{+\infty} \Psi(t) dt = 0 \quad (7.2)$$

$$\Psi_{s,\tau}(t) = \int_{-\infty}^{+\infty} \Psi(t)^2 dt = 1 \quad (7.3)$$

There exists a large number of wavelet families with different properties and applications that fulfil these characteristics.

Wavelet transforms are most commonly divided into Continuous Wavelet Transforms (CWT) and Discrete Wavelet Transforms (DWT). Both types can be applied to continuous time-series. The difference between these two transforms resides in the scaling factor: the CWTs are applied through all the possible scales and translations whereas DWTs operate on specific values. Hence, the application of CWTs provides the whole spectrum of frequencies present at each point of the time-series. In contrast, the DWTs return a specific frequency band, depending on the scaling factors employed. Consequently, the applications of the two kinds of transforms are significantly different: CWTs are often used in signal analysis, for example, to determine the cyclicity of a signal such as groundwater levels or climate indices (e.g. Coulibaly and Burn 2004; Massei et al. 2010); whereas DWTs are often used to denoise signals or decompose time-series (e.g. Smith et al. 1998; Sang et al. 2009).

In this chapter, CWTs are applied to analyse the cyclicity of groundwater levels and rainfall over the study areas, as well as the main modes of climate variability. The Wavelet Transform Coherence (WTC) is then used to study the relationship between signals. Both methods are described in detail below. Further discussion of DWTs and their properties are presented in Section 8.2.

7.2.1.1. Continuous Wavelet Analysis

The Continuous Wavelet Transform (CWT) presented above, can be mathematically expressed as:

$$\gamma_{s,\tau}(t) = f(x)\Psi_{s,\tau}^*(t)dt \quad (7.4)$$

where * stands for a complex conjugation, $f(x)$ is the function decomposed into basis functions $\Psi_{s,\tau}$ that are the wavelets (Eq. 7.1), s (scale factor) and τ (translation factor) represent the resulting dimensions.

If the transform is applied specifically to continuous time-series the equation (7.2) can be expressed as:

$$C_{s,\tau}(t) = \int_{-\infty}^{+\infty} x(t) \Psi_{s,\tau}^*(t)dt \quad (7.5)$$

where $C_{s,\tau}$ represents the resulting coefficients of transformation given by the convolution of the time-series ($x(t)$), with the complex conjugation of the daughter wavelet ($\Psi_{s,\tau}^*$), as defined in Eq. 7.1, to obtain a spectrum of frequencies expressed in real numbers.

In summary, when a CWT is applied to a time-series such as groundwater level, the mother wavelet is *shifted* through the entire signal (τ) for a specific set of *scaling* coefficients (s), ($s<0$ denotes compression of the wavelet, $s=1$ is the mother wavelet and $s>1$ represents an elongation). This process is then repeated for all the possible scaling coefficients within the signal to obtain a full representation in the time-frequency space, which is considered by several authors as the main objective of performing wavelet analysis (e.g.Meyer 1992; Percival and Walden 2006). The results are normally presented in scalograms, which are graphic representations of the scales present within the time-series considered and are used

to assess the periodicities contained in the signal. In these graphs, the high frequencies are represented by small scales, whereas large scales correspond to low frequencies.

Finally, because the CWT is applied to finite-length time series, errors occur at the extremes of the power spectrum (Torrence and Compo 1998). To account for these edge effects, a Cone of Influence (COI) is also represented in the scalogram. The COI represents the regions of the spectrum where the edge effects are important (Torrence and Compo 1998) and cannot be ignored (Grinsted et al. 2004). This area, where the border effects cannot be ignored, corresponds to the large scales and extremes of the studied time series and is represented by a shadowed area in the Figures presented below.

7.2.1.2. Wavelet Coherence

Wavelet Transform Coherence (WTC) is a measure of the correlation between signals in the time-frequency plane and is especially useful for analysing nonstationary signals (Torrence and Compo 1998). And consequently, WTC reveals locally phase locked behaviours between the two signals (Grinsted et al. 2004). The WTC between two signals X_n ($n=1....N$) and Y_n ($n=1...N$) can be formally expressed as:

$$WTC = \frac{|W_n^{XY}(s)|^2}{W_n^X(s)W_n^{Y*}(s)} \quad (7.6)$$

W_n^X and W_n^Y denote the CWT of X_n and Y_n , W_n^{Y*} is the complex conjugate of the CWT of Y (W_n^Y) and W_n^{XY} is the Cross Wavelet Transform (XWT) which can be calculated as:

$$W_n^{XY} = W_n^X(s)W_n^{Y*}(s) \quad (7.7)$$

And S is a smoothing operator:

$$S(w) = S_{scale}(S_{time}(W_n(s))) \quad (7.8)$$

where S_{scale} represents smoothing along the wavelet scale axis and S_{time} smoothing in time.

Coherence values can range between 0 and 1 where 1 indicates that the response energy is 100% and hence indicates a direct relationship between the inputs. Thus, another useful application of the wavelet coherence is to determine when to apply linear and non-linear modelling approaches (Chinarro et al. 2012).

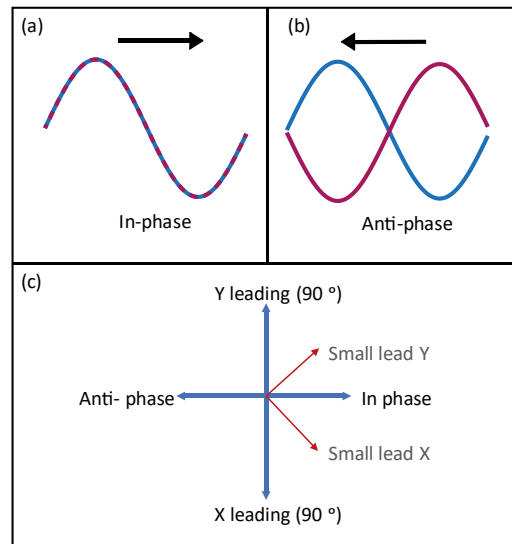


Figure 7.1: Graphical representation of the phase information contained in the WTC and the relative position of X (blue) and Y (red) graphs in (a) and (b).

In this study, the WTC has been calculated based on the MATLAB toolbox developed by Grinsted et al. (2004). The significance level of the WTC is estimated through Monte Carlo methods, at 95% confidence level. The results are presented in scalograms, where the phase relationship between the two signals is represented by arrows. In this way, horizontal arrows pointing right indicate in-phase relationships and pointing left indicate anti-phase relationships (Figure 7.1a and 7.1b). Similarly, downwards arrows indicate a time lag between the two signals where X is leading, and upwards arrows indicate a time lag with Y leading (Figure 7.1c). The length of this time lag depends on the angle drawn by the arrow.

There are other wavelet-based methods that could be used in a similar fashion, for example, the wavelet cross-spectrum or a combination of cross-correlation and CWT analysis. The wavelet cross-spectrum (XWT) reveals the areas of common power between two signals whereas the WTC displays areas with phase-locked behaviour. Hence, the XWT would just highlight the areas with common positive significant power but would disregard the areas with lower power but similar phase behaviour; this would provide a weaker notion of the linearity of the processes and causality between the two signals.

In its favour, the combination of cross-correlation and CWT would provide a similar phase-locked information through the cross-correlation as well as the spectral information contained in the CWTs. Nevertheless, to obtain the same amount of information as with the WTC, the cross-correlation should be applied to previously decomposed time-series (see Section 8.2.2) that would then need to be individually compared to the CWTs, complicating the interpretation of the results.

7.2.2. Climate Indices

In this study, data for five relevant teleconnection patterns have been used according to Barnston and Livezey (1987) and other bibliography sources (Hurrell 1995; Fang Z-F. 2004; Knight et al. 2006; Holman et al. 2011; Simunek et al. 2012; Comas-Bru and Mcdermott 2014; Zubiate et al. 2017): (1) Atlantic Multidecadal Oscillation, (2) the North Atlantic Oscillation, (3) the East Atlantic Pattern, (4) the Scandinavian Pattern, and (5) the Greenland Blocking Index, and are described below.

The **Atlantic Multidecadal Oscillation** (AMO) is a near-global scale mode of multidecadal climate variability alternating warm (positive) and cool (negative) phases (Knight et al. 2006). This climate cycle manifests itself by sea surface temperature anomalies of the North Atlantic Ocean. It has a quasi-cycle of 70 years approximately (ranging between 50 to 90 years) and is correlated with changes in rainfall and temperature patterns over the northern hemisphere (Wyatt et al. 2012). For instance, Knight et al. (2006) found that the AMO can explain between 30-40% of the observed low-frequency variance in temperature in central England. Positive (warm) phases of the AMO have been associated with exceptionally wet summers in Western Europe, whereas negative phases can be linked to dry summers (Sutton and Hodson 2005).

The **North Atlantic Oscillation** (NAO) is one of the most important teleconnection patterns across all seasons (Barnston and Livezey 1987), and it is considered as the principal low-frequency mode of climate variability in the North Atlantic region. The NAO is defined by the presence of a north-south dipole anomaly in pressure with one centre located approximately over the Azores and another over Iceland. These anomalies are known to affect the intensity and location of the North Atlantic jet stream and storm track (Hurrell 1995) which, in turn, affect precipitation patterns over Europe and eastern United States. Even though the NAO

has been traditionally calculated by the difference in atmospheric pressure between the two meteorological stations (Portugal and Iceland), in this study the PCA-based NAO has been used (Hurrell 1995). In a positive phase, the above-average atmospheric pressure system is located over the Azores, and below-average pressure over Iceland whereas a negative phase presents an inverted pattern of pressure anomalies. A positive NAO phase is generally linked with increased westerly winds, leading to above-average winter temperatures and precipitation, and below-average summers (Figure 7.2). In contrast, negative NAO phases are associated with low westerlies, which is translated into below-normal winter temperatures and precipitation, and above-normal summer temperatures (Hurrell 1995; Wanner et al. 2001; Comas-Bru and Mcdermott 2014). Nevertheless, this relationship is not always clear because of the interactions with other climate patterns such as the East Atlantic Pattern (EA) and the Scandinavian Pattern (SCA) that are described below (Wilby et al. 2000; Comas-Bru and Mcdermott 2014; Zubiate et al. 2017).

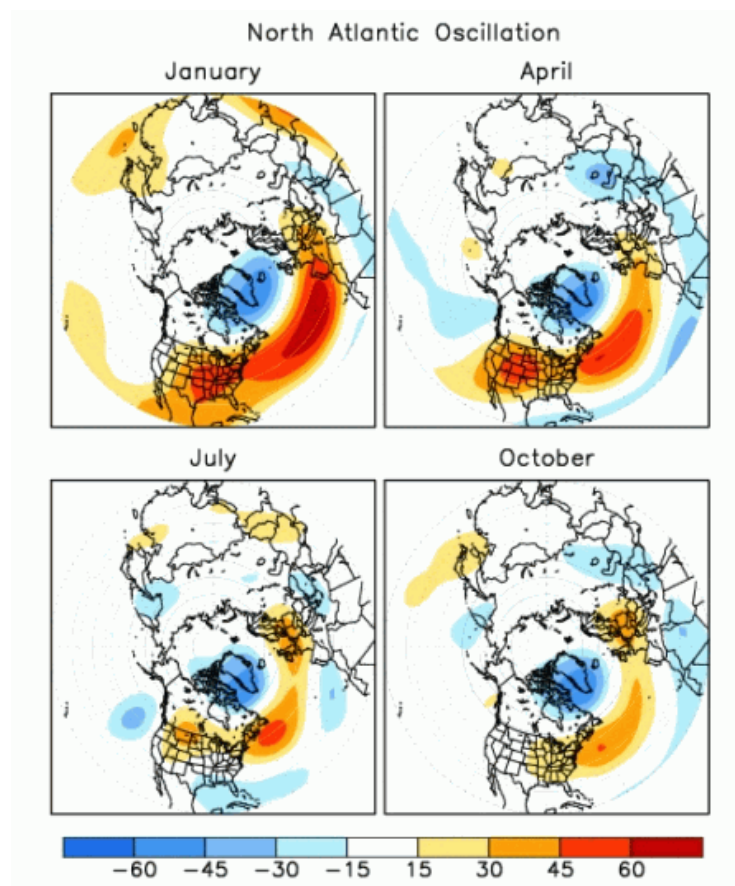


Figure 7.2: Seasonal effect of the NAO. Source: www.cpc.ncep.noaa.gov

The second most significant mode of climate variability in the North Atlantic regions is the East Atlantic Pattern (EA). Similarly to the NAO, the EA pattern presents a dipole structure but with the centres of action displaced towards the southeast (Barnston and Livezey 1987).

When the EA is positive, above-average temperatures occur in Europe for all months, with also increased precipitation for northern Europe and Scandinavia but below-average precipitation in the Mediterranean regions (CPC 2012; Moore and Renfrew 2012; Comas-Bru and Mcdermott 2014).

The **Scandinavian Pattern** (SCA) is considered to be the third low-frequency leading mode of climate variability in the North Atlantic Region, and is equivalent to the Eurasia-1 pattern described in Barnston and Livezey (1987). This pattern has its primary centre of action around the Scandinavian Peninsula, with two other centres of opposite sign over the north-eastern Atlantic and central Siberia (Bueh and Nakamura 2007). A positive SCA is generally associated with above-average precipitation and below-average temperatures (CPC 2012). However, Bueh and Nakamura (2007) found that there are significant negative anomalies around the UK and Ireland in January, whereas these anomalies tend to be positive for October and April, with an overall increase in precipitation in the cool seasons over the north-eastern Atlantic.

The last mode of climate variability considered in this study is the **Greenland Blocking Index** (GBI), which is closely linked to the NAO. The GBI was firstly defined by Fang Z-F. (2004) and consists of a high-pressure blocking system over Greenland. There is a strong negative correlation between the GBI and the NAO, and some authors hypothesize that negative NAO is caused by Greenland blocking whereas a positive NAO phase is merely reflecting the absence of blocking (Woollings et al. 2008; Davini et al. 2012; Hanna et al. 2018). Thus, a positive GBI phase has - in practical terms - opposite climate effects than the NAO. Consequently, opposite effects to the NAO are also expected on the groundwater resources. Nevertheless, to the knowledge of the author, the effect of this index on groundwater has never been investigated so the previous statement constitutes a hypothesis that needs to be verified.

All the climate indices data have been obtained from the KNI Climate Explorer website (<https://climexp.knmi.nl>) at monthly resolution. The Spearman rank correlation has been used to assess the relationship of each index with mean seasonal rainfall for each study area.

7.3. Results

In this section the results obtained for the Knocktopher, the Mattock and the Dripsey study sites are presented. For clarification, and in order to avoid confusion, the reader should note that the time-series used for the Knocktopher (1995-2019) is longer than those analysed for the Mattock and the Dripsey (2008-2018) and consequently, the X axis of the figures is different between the former and the latter. Note also that this difference in the time-series length affects the Y axis in the case of the scalograms, as longer periods are represented on the graphics.

7.3.1. Continuous Wavelet Analysis

The results obtained from applying the CWTs to the time-series are represented in scalograms, which can be understood as 3-D representations of the wavelet coefficients obtained from the transformations. In this way, the X-axis represents the time, the Y-axis represents the scale or frequency and the colour scale represents the logarithm of the squared modulus of the wavelet coefficients, that is to say, how well a given frequency is represented within the signal.

The scalograms obtained from the CWTs of the rainfall series for the three study sites display statistically significant areas (black contour) of high power (Figure 7.3 (a,d,g)). These high-power patches correspond to particularly wet seasons when associated with periods shorter than 8 months (Figure 7.3), or an annual periodicity if the corresponding periods fall between the 8 and 16 months. Because these high-power areas are discontinuous, they point to exceptionally wet years rather than to an annual cyclicity in the rainfall.

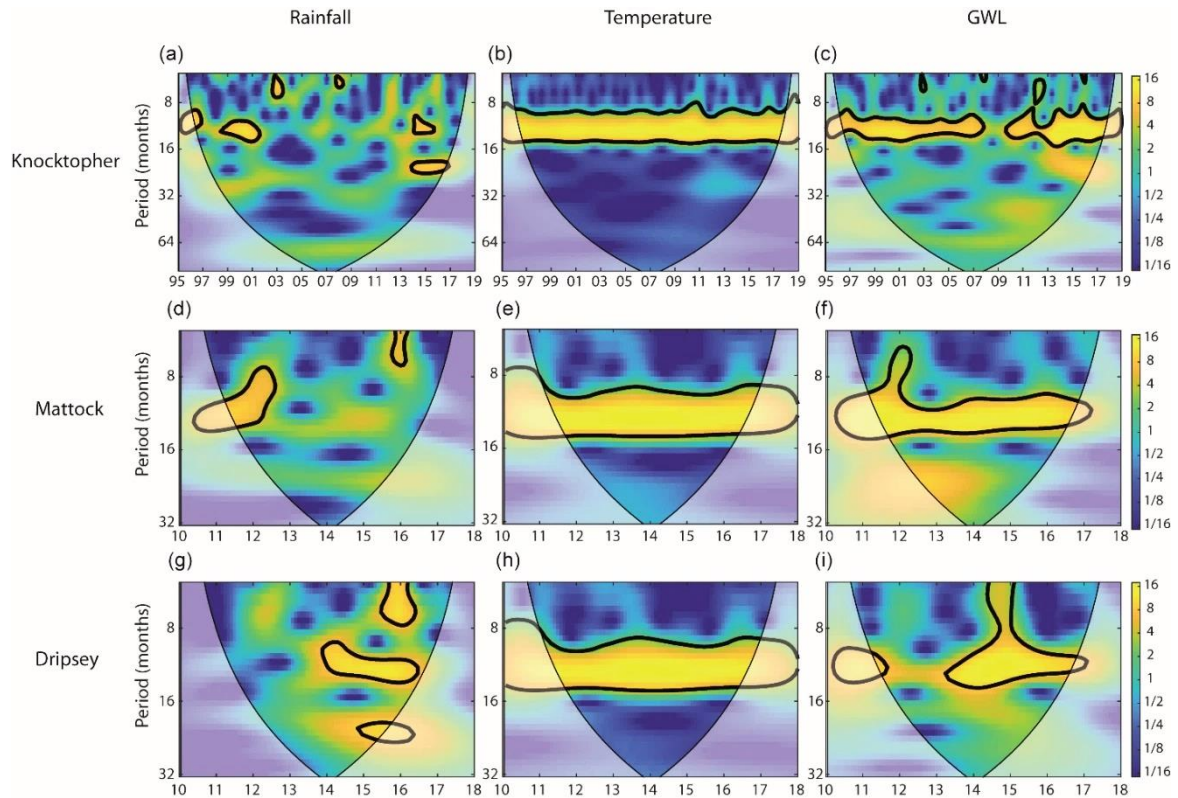


Figure 7.3: Scalograms of the rainfall (first column), average monthly temperature (middle column) and groundwater levels (last column) for the Knocktopher (top row), the Mattock (middle row) and the Dripsey (bottom row). The 95% significance areas are marked in black, and the COI is shadowed in grey. The X-axis shows the year (where the year has been shortened to the two last digits for better readability)

Moreover, these areas highlight the strong regional component of the rainfall distribution as they appear at different times for the three study areas. In contrast, the scalograms of the temperature time-series are remarkably similar; in the three cases, there is a single and continuous high-power area associated with 12 months periods and hence, indicating a strong annual cyclicity (Figure 7.3 (b,e,h)).

Finally, the scalograms corresponding to the groundwater levels show a combination of the features observed in the rainfall and temperature scalograms (Figure 7.3 (c,f,i)): whereas some of the specificities can be linked to the rainfall, the groundwater levels (GWL) of the three sites show a clear annual cyclicity, being especially strong at the Knocktopher site but discontinuous in the Dripsey catchment. Furthermore, the rainfall specificities of the Knocktopher and the Dripsey can be identified in the corresponding GWL scalograms whereas this is not possible for the Mattock that attenuates part of the signal. These discrepancies could denote differences in the infiltration processes between the three catchments.

7.3.2. Wavelet Coherence

7.3.2.1. *Groundwater Levels and Rainfall signal*

Similarly to the CWTs, the WTC results are also plotted in scalograms. However, in this case the colour scale represents the correlation between the two signals, where the maximum value is 1 (yellow), and indicates a strong linear relationship between the two signals, whereas the minimum possible value is 0 (dark blue) and highlights the different behaviour of the signals. Additionally, the phase relationship between the two variables is represented by arrows, as described in Figure 7.1.

Figure 7.4 shows the scalograms resulting from the application of the WTC, comparing rainfall and groundwater levels at daily resolution. The three monitoring points present a similar pattern: a first area of alternating thin vertical coherence strips with non-coherent bands (0-32 days); a second area from 32 days where these coherence strips start to become thicker and connect between them; and a third area from 128 days where these areas tend to re-arrange in horizontal bands of coherence connected in different measures between them. These three areas within the graphs represent the infiltration process at short, medium and long-term respectively, and are further discussed below.

The first area (0-32 days) represents the infiltration processes at sub-monthly scale. The areas where there is a linear relationship between the rainfall and the groundwater levels (yellow) correspond to recharge events in the hydrographs plot above the corresponding WTC, whereas the non-coherent areas represent recessions (blue). In the case of major water level recessions, their effect can be traced for longer periods, for example, the recession of 2011 in the Mattock (Figure 7.4b) has an effect up until 128 days (4 months). This intercalation reflects the intrinsic non-linearity of the infiltration processes due to, among other causes, the hysteresis of the drying-wetting curve. This first area is distinguishable in the three catchments but is more evident in the Knocktopher and the Mattock, where the relationship with the groundwater levels described above can also be observed more clearly.

In the second area (32-128 days), which reflects the monthly to seasonal behaviour, the coherence areas tend to blend forming larger areas. The phase arrows point mostly right-downwards, indicating that the two signals are in phase, but that there is a lag between rainfall and groundwater levels as would be expected. This time lag varies between different recharge periods and between catchments. For instance, the lag appears to be longer in the Knocktopher than in the Mattock. However, this relationship is not clear in the Dripsey where it is not possible to establish a phase pattern.

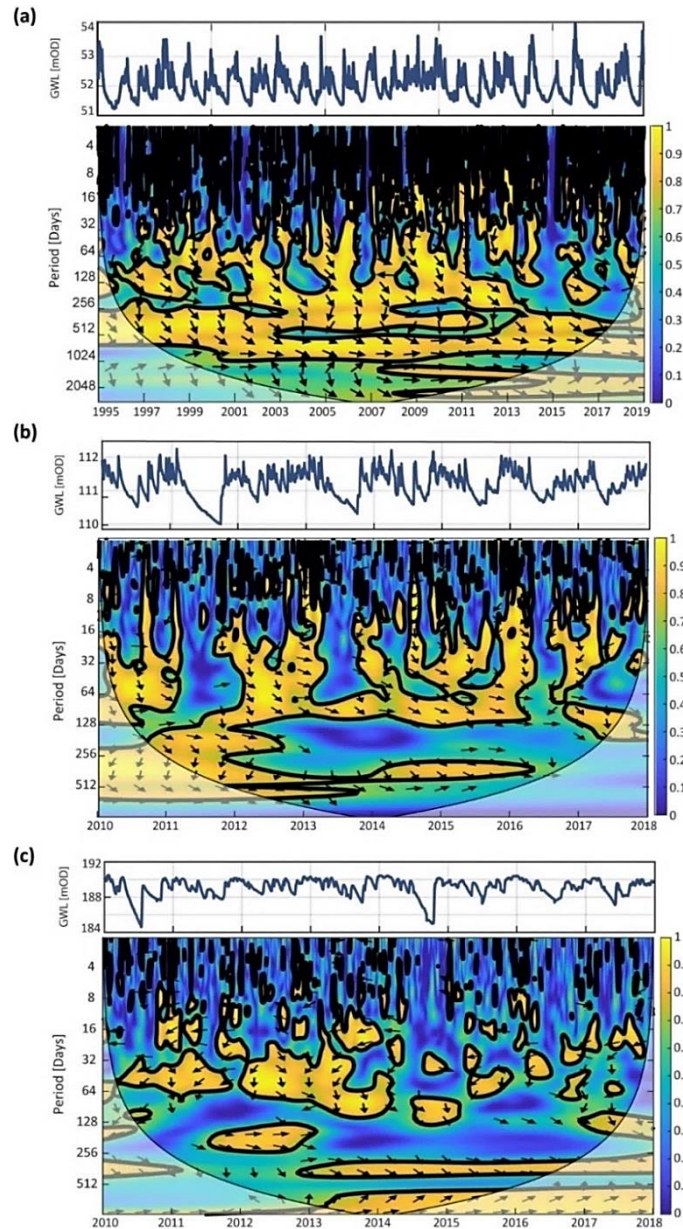


Figure 7.4: Groundwater level time-series and rainfall -GWL wavelet coherence for (a) the Knocktopher, (b) the Mattock (MK1-shallow) and (c) the Dripsey (DR1-Sahllow) boreholes. The 95% significance areas are marked in black, and the COI is shadowed in grey

For periods of 4-8 months onwards (128-256 days), the coherence bands are disposed horizontally as well as the phase arrows, indicating that at these longer time scales the time lag between rainfall and groundwater levels is negligible. However, this region is the most variable between catchments as it represents the long-term behaviour of the aquifer: at Knocktopher, there is a fairly continuous band extending from 8 months to almost 3 years (256-1024 days) onwards, suggesting a strong annual and multi-annual cyclicity during the period under consideration. In contrast, in the case of the Mattock, there are two relevant bands: a first strip that occurs for shorter periods (128 days) indicating a seasonal cyclicity, and a second one between 256-512 days suggesting there is also an annual periodicity (although this is not present through all the time-series, and the phase is affected by the long recessions). Finally, the Dripsey presents a rather continuous band of coherence corresponding to an annual cyclicity, where the phase arrows point at a direct relationship with a short time lag. Another band appears for longer periods, suggesting that there is a multiannual periodicity, but it is at the limit with the COI, so it must be interpreted with caution.

It is clear from the graphs, that the Dripsey (Figure 4.3c) presents a somewhat different behaviour for the short to medium periodicities with more non-linearities and, consequently, a less direct relationship between the rainfall and the groundwater levels. These differences can be interpreted as a consequence of an important dampening of the signal due to the presence of a well-developed transition zone (TZ), as it is known to be a preferential pathway (see Section 3.2.3). The TZ would divert most of the infiltration laterally as interflow reducing the amount of potential recharge transiting vertically towards the water table. Thus, the short-term response of the system is generated by the TZ, dampening the recharge signal into the shallow bedrock, which is also illustrated by the phase arrows which generally present long time lags, reaching an anti-phase position for frequencies below a month. This hypothesis was then confirmed by performing the WTC to a borehole installed in the transition zone of the Dripsey (Figure 7.5), where the short term coherence areas can be linked to water table fluctuations, and the overall WTC presents similarities with those obtained for the Knocktopher and the Mattock.

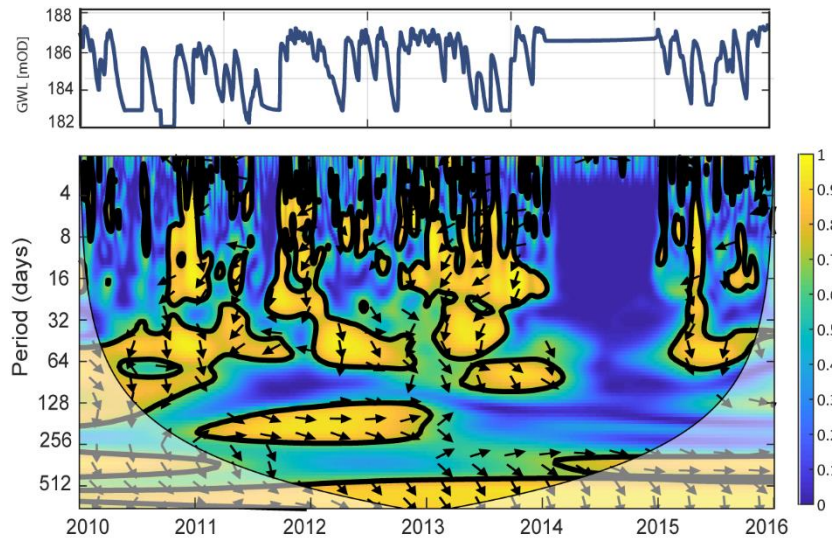


Figure 7.5: Groundwater level time-series and rainfall - GWL wavelet coherence for the Transition Zone borehole (DR2-TZ) at the Dripsey catchment. The 95% significance areas are marked in black, and the COI is shadowed in grey

7.3.2.2. Groundwater Levels and Teleconnection Indices

The results presented for the CWTs (Section 7.3.1) have highlighted the regional differences of the rainfall characteristics and spectral signature and the different responses of the aquifers to it. Furthermore, the WTCs presented in the previous section have revealed important differences between the aquifers' hydrogeological behaviour so contrasting responses of the catchments to the teleconnection indices are anticipated. In order to determine if the features present in the groundwater level WTC spectrograms are due to local rainfall variability or the local hydrogeological characteristics, the WTCs have also been applied to compare the indices and the rainfall. Thus, if a feature can be identified in the rainfall WTC, this denotes a climatic cause, whereas if it is just present on the groundwater level WTC it would suggest that it is related to the aquifer's properties. In this way, a figure for each borehole is presented, where the indices-rainfall WTC is shown in the first column and the indices-GWL in the second, and each row corresponds to a different climate index (see Figures 7.7 to 7.9).

Given that the time-series available for the Knocktopher site are longer, the results obtained for this borehole are used for the general interpretation of trends, and longer-term effect of the different climate indices on groundwater resources in Ireland. The Mattock and the Dripsey are interpreted as study cases to analyse in detail the differences caused by their distinct physical properties. Finally, Figure 7.6 shows the Spearman rank correlation used to

assess the relationship of each index with mean seasonal rainfall for each study area. The results are first discussed index by index in the following order: AMO, NAO and GBI, EA and SCA. Then, a short summary by site is presented as a synthesis of the main findings.

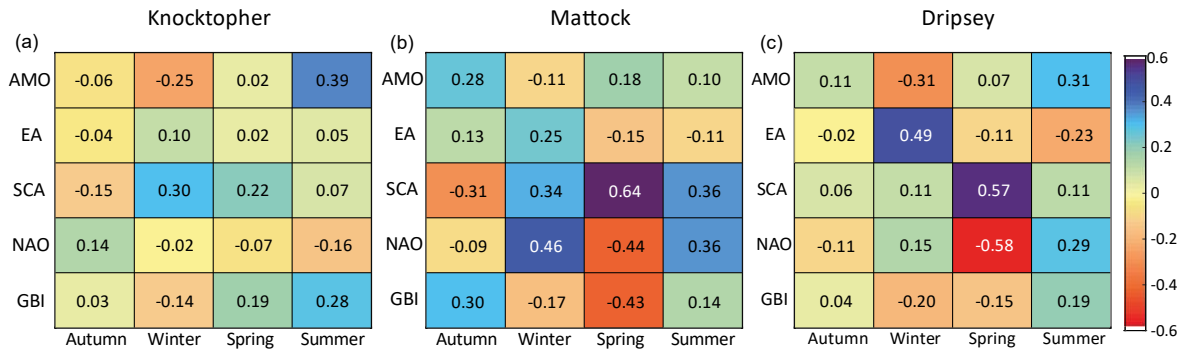


Figure 7.6: Heatmap of the Spearman coefficients for each climate index and seasonal rainfall in a) the Knocktopher, b) the Mattock and c) the Dripsey boreholes. Dark blue and purple indicate strong positive correlations, whereas red denotes a strongly negative correlation.

a) *Atlantic Multidecadal Oscillation (AMO)*

Figures 7.7b, 7.8b and 7.9b present the resulting AMO-GWL WTCs for the Knocktopher, Mattock and the Dripsey boreholes, respectively. Most of the significant coherence areas can be linked to the respective rainfall spectrograms (Figures 7.7a, 7.8a and 7.9a). Nevertheless, an important amplification of the signal is observed in the GWL spectrograms, which is especially significant in the Mattock (Figure 7.8b). This amplification is interpreted, on the one hand, as a consequence of the difference in time scales between the rainfall events and the recharge processes and, on the other hand, it may be due to the aquifer system's long 'memory effect' as shown by the high autocorrelation of the GWL (Section 6.3.2).

The Spearman ranked correlation shows a clear seasonal fingerprint in the three study sites (Figure 7.6). At Knocktopher and Dripsey, the signals during autumn and spring are weak, and stronger in summer and winter. In this way, a positive AMO would be related to increased summer precipitation and lower winter precipitation, as expected. Nevertheless, the seasonality is shifted for the Mattock, which presents a stronger correlation in autumn and spring (both suggesting increased precipitation) and weaker in winter (lower precipitation) and summer.

The Knocktopher AMO-GWL spectrogram (Figure 7.7b) shows scattered patches of coherence corresponding to 0-8 months periods. The phase arrows are mostly pointing right

downwards suggesting a direct relationship with a variable time-lag between the AMO (X) and the GWL (Y).

The areas where this relationship is inverted and phase arrows are pointing upwards (Y leading), correspond to non-stationarities of the AMO, changing towards negative phases as it occurs in the 1995-1997 period. In such periods, the observed rainfall pattern does not match with what we would expect from a fully negative phase (Figure 7.10a).

The seasonal fingerprint revealed by the correlation is represented by the significant coherence areas with corresponding 4-8 months periods, that can be linked directly to the peaks in the AMO signal. The phase arrows point generally downwards but the angle varies from in phase to antiphase (Figures 7.7b, 7.8b and 7.9b). These phase variations are due to the seasonality of the AMO: where the phase arrows are trending towards in-phase positions, the AMO peaks in Spring/Summer causing increased precipitation. In contrast, in areas trending towards anti-phase the AMO peaks occur in winter and/or autumn, causing a reduction in precipitation.

The effect of these peaks on the groundwater system depends on the persistence of the AMO signal: a prolonged high AMO phase causes longer lasting effects on the GWL where coherence areas have associated periods between 6-12 months (2002-2004). In this way, relatively short high positive AMO periods (2007) have a shorter effect, with associated periods around 4-6 months. Finally, the high coherence area corresponding to the 2.5-5 years (32-64 months) could suggest another periodicity (7.7b). Nevertheless, this coherence region could be reflecting the predominant negative phase of the AMO over the 1980's and 1990's not represented in this graph, as the phase arrows are pointing upwards. However, this area is outside the COI and hence, is susceptible to border effects.

Overall, the Mattock catchment presents larger coherence areas and so, the AMO signal appears to be more strongly represented by the presence of two interconnected large coherence regions affecting all the frequencies at the beginning of the time series (2010-2013) (Figure 7.8b).

However, AMO is linked with sea surface temperatures and, consequently, it would be expected to have a larger effect on the sites closer to the coast such as the Dripsey. In fact, the Spearman correlation shows weaker AMO influence in the Mattock, where the strongest signal is shifted to autumn instead of summer.

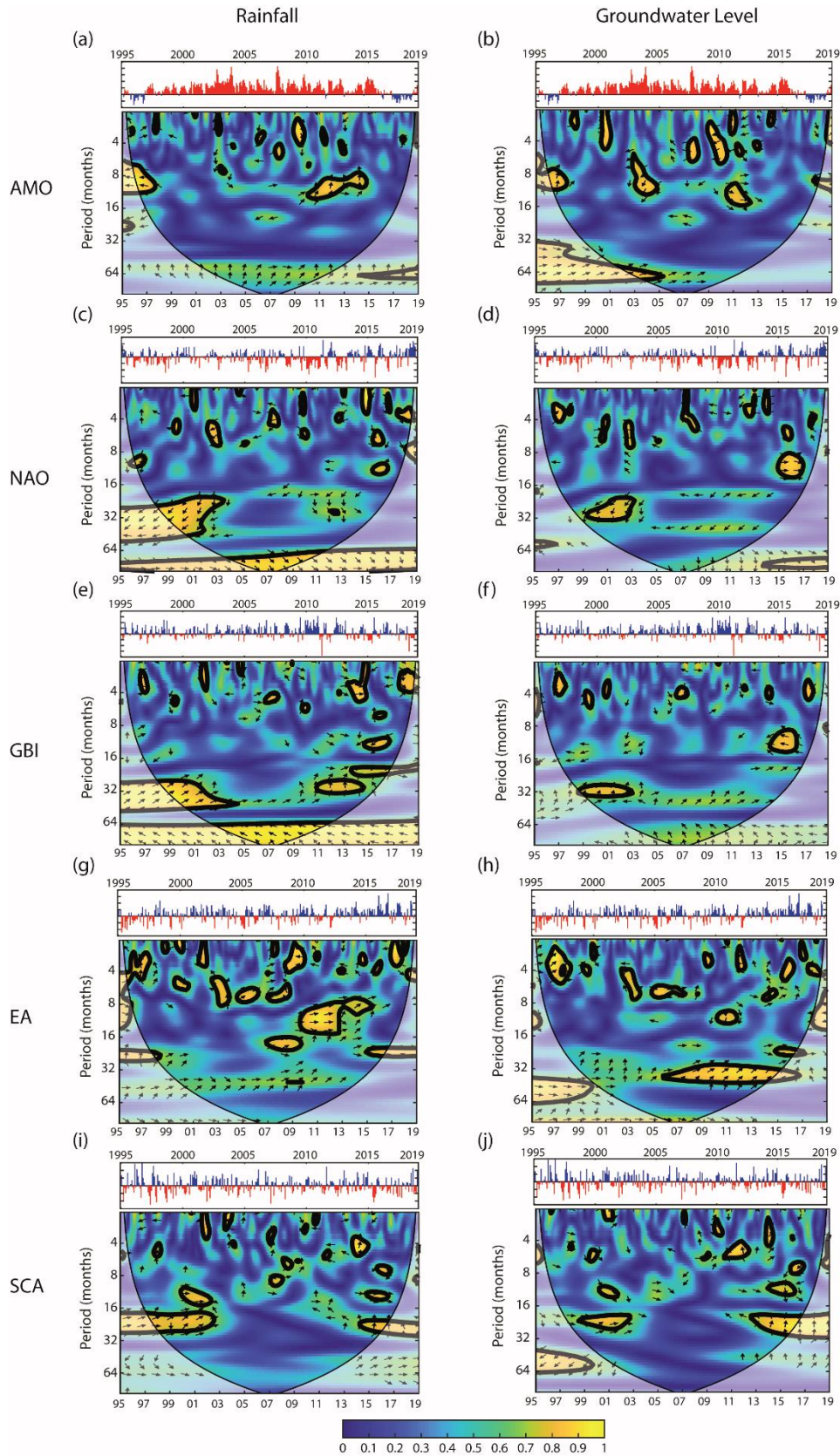


Figure 7.7: Temporal evolution of the teleconnection indices and index-rainfall wavelet coherence (left column) and index-GWL coherence (right column) at the Knocktopher borehole site. The 95% significance areas are marked in black, and the COI is shadowed in grey. (The years have been shortened to the last two digits for better readability).

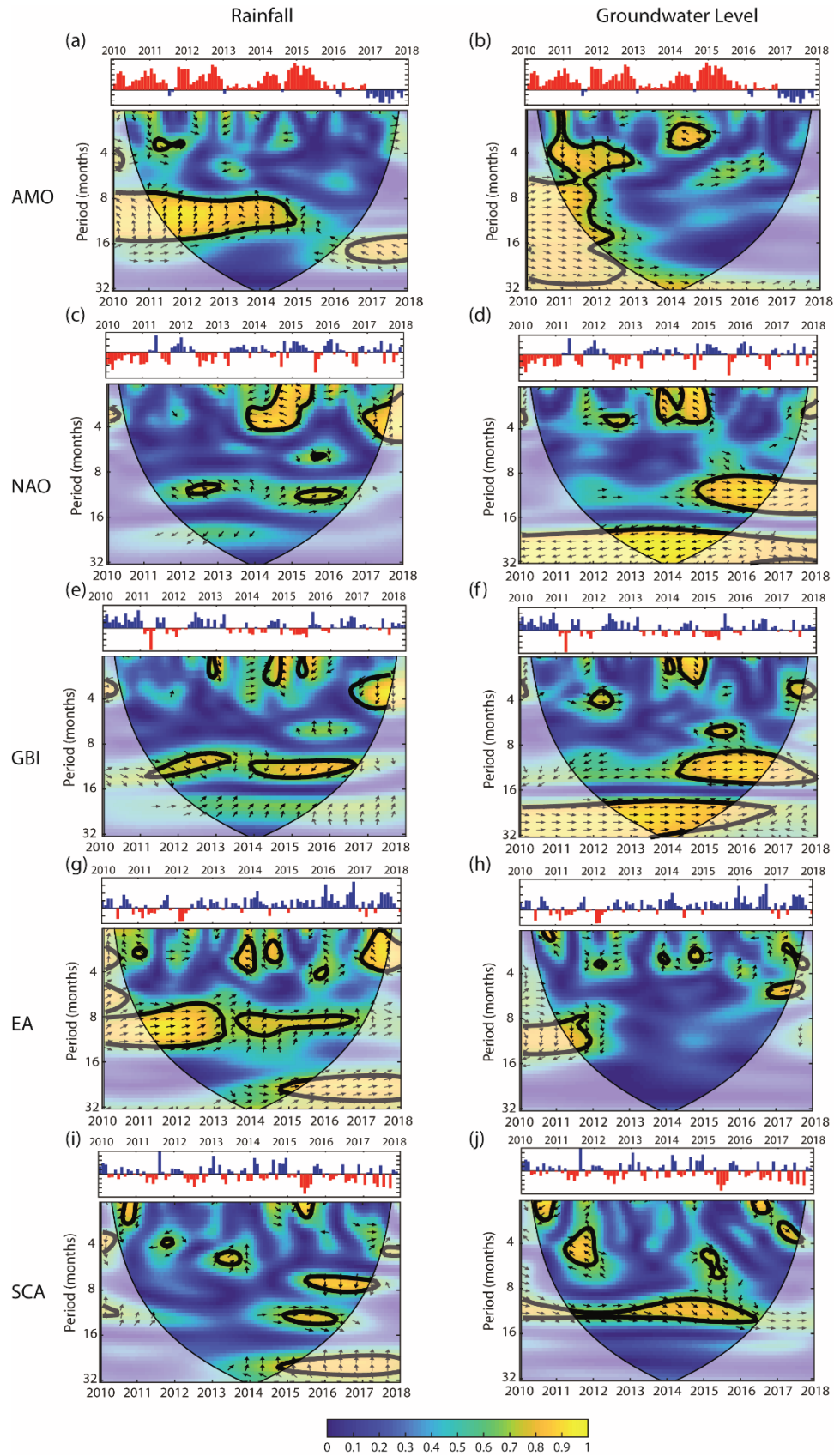


Figure 7.8: Temporal evolution of the teleconnection indices and index-rainfall wavelet coherence (left column) and index-GWL coherence (right column) in the Mattock catchment borehole. The 95% significance areas are marked in black, and the COI is shadowed in grey.

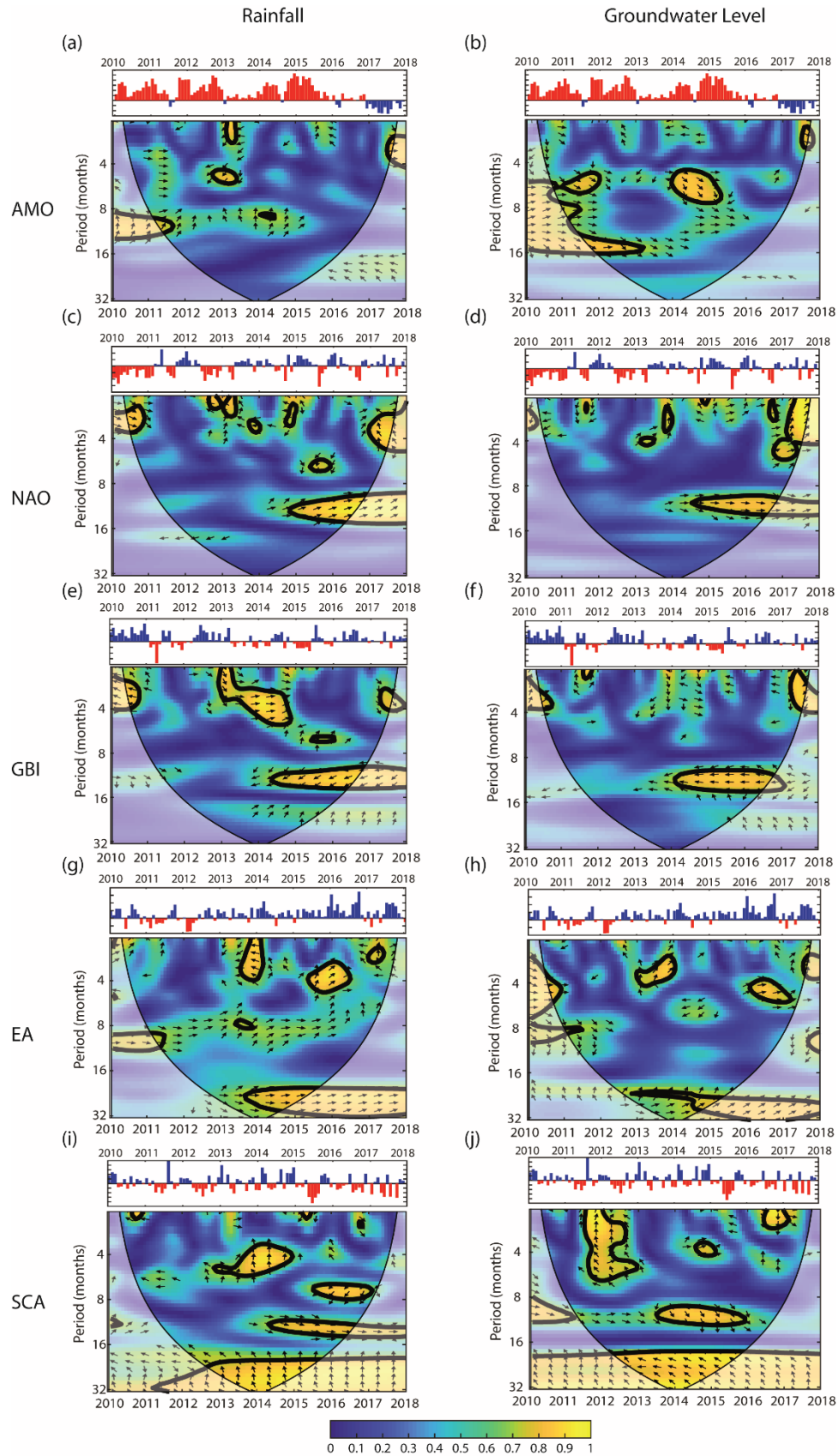


Figure 7.9: Temporal evolution of the teleconnection indices and index-rainfall wavelet coherence (left column) and index-GWL coherence (right column) in the Dripsey catchment borehole. The 95% significance areas are marked in black, and the COI is shadowed in grey.

Of the two large areas identified, the first area can be linked to a particularly wet autumn of 2010, matching with high AMO positives. This, in turn, could be a consequence of the shifted seasonality at the Mattock as an exceptionally wet autumn would generate large recharge events. In contrast, a strongly positive AMO during autumn 2010 would have little effect on the other catchments as they present a low correlation (Figure 7.6), which is evidenced by Figure 7.10 that shows below average precipitations for this period.

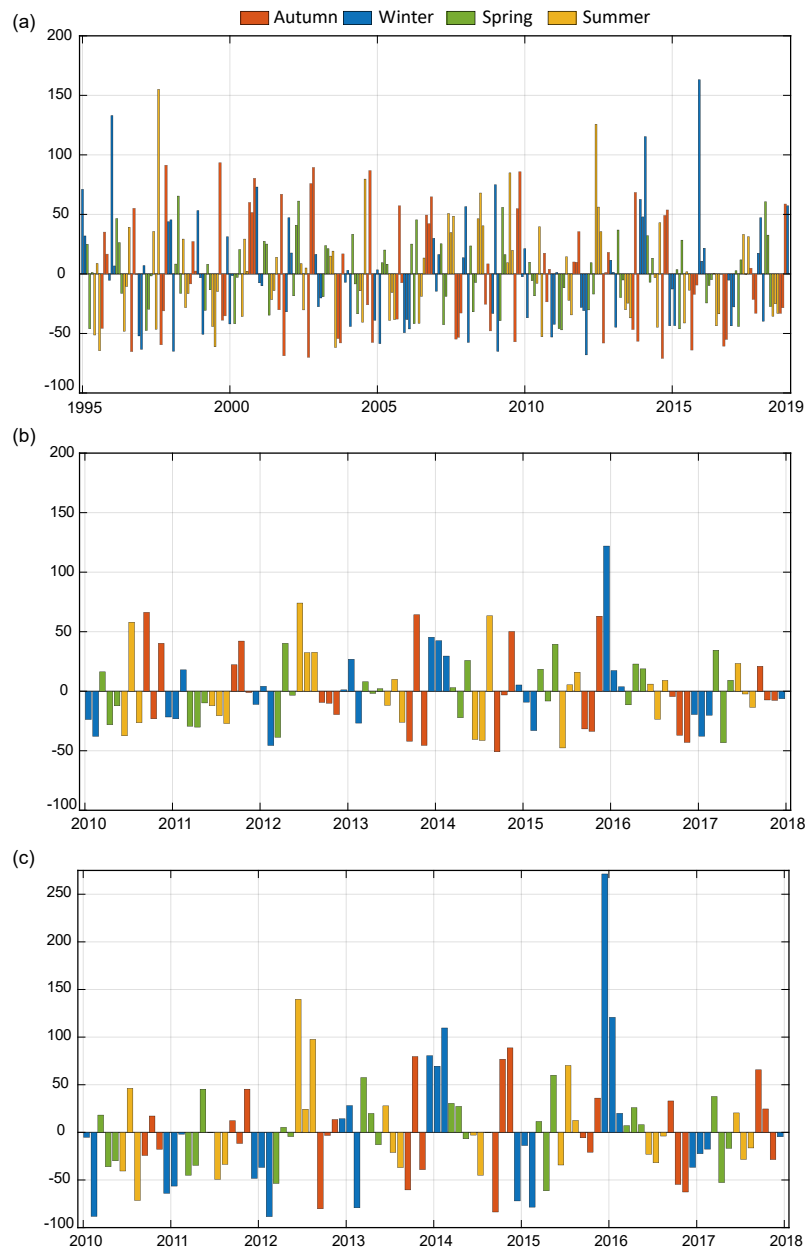


Figure 7.10: Seasonal rainfall anomaly expressed in mm/month for a) the Knocktopher, b) the Mattock and c) the Dripsey study sites.

The second area affects lower frequencies corresponding to 6-24 months, and it represents the seasonal to multiannual effect of the positive AMO phases in the Mattock GWLs: this

indicates that the recharge events of autumn 2010 mentioned above, had a long-term impact on the groundwater levels. Rainfall – and recharge - events are more likely to have a long-lasting impact on the GWL if they occur during autumn rather than in summer as the PE and T are normally lower, rainfall is typically higher, and the soil is less likely to be in moisture deficit. Consequently, rainfall is more likely to reach the water table becoming actual recharge.

b) North Atlantic Oscillation (NAO) and Greenland Blocking Index (GBI)

Given the strong (negative) correlation between the NAO and GBI, the interpretation of the results is presented jointly. The Spearman coefficients indicate that there is a weak correlation of the NAO in the Knocktopher, whereas this is notably strong in the Mattock (see Figure 7.6). The Dripsey presents a strong negative spring correlation, and moderate positive summer and winter correlations (Figure 7.6). In general, the Mattock is the study site with the strongest correlation with the NAO index and, consequently, the corresponding scalograms should reflect a larger effect from the NAO than the other study sites.

Overall, the positive (negative) phases of the NAO are represented in the WTC with in-phase (antiphase) arrows (Figure 7.7d, 7.8d and 7.9d). In addition, the non-stationarities - or brief positive NAO phases - are translated into the scalograms with a shift on the phase arrows, indicating a larger time lag. In the case of the Knocktopher (Figure 7.7d), there is an important attenuation of the signals present in the NAO-Rainfall scalogram (Figure 7.7c), which is especially significant at annual and multiannual scales. The only specificity at this range of frequencies that is amplified is the one corresponding to the winter NAO of 2015-2016, which presents an in-phase relationship. Consequently, there are no long-term periodicities present in the NAO-GWL spectrogram.

In contrast, this attenuation is weak in the case of the Dripsey whereas a clear signal amplification occurs at the Mattock (Figure 7.8d and Figure 7.9d). Additionally, a clear annual cyclicity can be observed in both the Mattock and the Dripsey from 2015, coinciding with the start of a generally positive NAO phase. These areas present in-phase arrows, indicating increased groundwater recharge, so they denote the impact of Winter NAO.

Interestingly, there are a few cases where the phase arrows are orientated upwards (GWL leading) despite belonging to a NAO positive phase. In these cases, the rainfall patterns do not match with what we would expect from a positive phase of the NAO (i.e. winter is relatively dry despite a clear positive signal). This is the case for the Mattock during the 2015-2017 period when the NAO was predominantly positive (Figure 7.8d) but the rainfall anomalies for 2015 and 2017 show below-average winter rainfall (Figure 7.10). This would suggest interference with other patterns or that the phase relationship is affected by non-stationarities as mentioned above.

Furthermore, the Mattock NAO-GWL spectrogram presents a continuous coherence band corresponding to periods between 2.5 and 5 years with a predominantly anti-phase relationship (Figure 7.8d). This could be reflecting the generally negative NAO phase through the time series as phase information becomes inconsistent in positive periods. However, this band is not present in the NAO-Rainfall spectrogram which implies a large amplification of the signal from the aquifer system (Figure 7.8c).

Finally, the spectrograms obtained from the GBI present the same coherence areas as the NAO, with a slightly higher attenuation of the signals and in perfectly opposite phases (Figure 7.7f, 7.8f and 7.9f). This is consistent with the findings of Woollings et al. (2008) and Hanna et al.(2018), as the occurrence of one implies the absence of the other or, in other words, the two indices mirror each other.

c) East Atlantic Pattern (EA)

The East Atlantic Pattern (EA) presents a complex behaviour in the three study areas that complicates identifying patterns, both in terms of periodicities and phase relationships. The Spearman coefficients reveal an extremely low correlation at the Knocktopher, as the highest value is 0.1 for winter (Figure 7.6). Nevertheless, there is a strong positive winter correlation for the Dripsey as well as an important negative summer correlation. For its part, the Mattock presents a moderate correlation which is positive in winter and Negative in summer.

Given the correlations obtained, a positive EA phase would imply enhanced winter groundwater recharge and decreased summer recharge. Therefore, positive EA phases should be represented with in-phase arrows in the wavelet coherence. However, there is no

clear phase relationship, probably due to the high non-stationarity of the EA and/or to its concomitant state in relation to the NAO.

Most of the significant coherence areas present in the EA-GWL spectrograms (Figure 7.7h, 7.8h and 7.9h) can be identified at the respective EA-Rainfall WTCs (Figure 7.7g, 7.8g and 7.9g). However, there is an important attenuation of the signals for frequencies between 16 and 32 months (1-3 years approximately) which, in some cases, leads to the disappearance of large coherence areas in the groundwater levels signal in the Mattock and at Knocktopher. The latter also shows a large amplification of the long-term rainfall signal (over 32 months) by transforming non-significant areas into large areas of coherence.

Even though the Mattock presents the damping of similar frequencies in the AMO, this is not the case for the NAO and GBI. Conversely, the Knocktopher borehole record does not show attenuation for these frequencies for the AMO but does for the NAO and GBI. Consequently, these differences cannot be explained by physical properties of the study sites. For its part, the Dripsey displays a contrasting behaviour with the appearance of some coherence areas that are not present on the rainfall scalogram (Figure 7.7g, h).

d) Scandinavian Pattern (SCA)

Figures 7.7j, 7.8j and 7.9j present the resulting SCA-GWL WTCs for Knocktopher, the Mattock and the Dripsey, respectively. The Spearman's rank correlation indicates that the three boreholes present a moderate to strong positive spring correlation, and weak to moderate positive correlations for spring and summer (Figure 7.6).

The Dripsey catchment, displays a complex pattern for periods up to 8 months, for which certain specificities are amplified and others erased in the same range of frequencies. It is difficult to establish a phase relationship or a seasonal fingerprint for these ranges of frequencies.

Nevertheless, there is an evident annual periodicity in the Mattock, which is an amplification from the rainfall signal (Figure 7.8i), which is also observed in the Dripsey though it is less continuous (Figure 7.9i). The phase arrows point towards a direct relationship with a time lag (X leading) and can be correlated with positive SCA winters.

The Knocktopher does not display a clear annual periodicity but a rather discontinuous two years cyclicity, with phase arrows pointing upwards. Similarly, the Dripsey presents a large and continuous band of coherence through all the time series from approximately 20 months onwards, with upwards antiphase arrows. This specificity is not observable for the Mattock.

Finally, the Knocktopher site displays an amplification of the long-term signal with associated periods of approximately 5 years (32-64 months), suggesting the presence of another potential periodicity. However, this area is discontinuous and is outside the COI, so it must be interpreted with caution.

e) Summary

The results presented during this section have demonstrated that each study site presents a higher sensitivity to specific indices and, consequently, the signal observed in the index-rainfall WTC can be either reduced or amplified depending on such sensitivity.

The Knocktopher borehole shows a complex pattern of reduction/amplification of the rainfall signal for specific ranges of frequencies, that also varies among the indices (Figure 7.7); In the case of the AMO, it is consistent with the AMO-Rainfall scalogram, but it presents an important amplification of the long-term periodicity. Conversely, there is a strong attenuation of the mid to long-term signals associated with the NAO and GBI. However, the most complicated attenuation/amplification pattern corresponds to the EA, where the signals corresponding from 8-32 months are almost erased but there is an important amplification of the multiannual frequencies (> 32 months). Finally, a slight attenuation of the bi-annual periodicity can be observed for the SCA whereas there is an amplification of the multiannual signal, even though this is affected by the COI. Generally, the attenuation of the signal occurs for indices with particularly low correlations such as the EA or the NAO. Given the weak effect of these indices from monthly to seasonal timescales, it is plausible that the effect of these indices does not extend to longer periods.

The results obtained for the Mattock borehole are presented in Figure 7.8, which displays an overall amplification of the rainfall signals, especially for the NAO as it presents strongly positive winter and summer correlations. Similarly, there is an amplification at the beginning of the AMO time-series, attributed to the shifted seasonality of the index in the Mattock, as

well as an amplification of the annual periodicity of the SCA. Nevertheless, the longer-term signal (16-32 months) for the second half of the time-series (2015-2018) is suppressed in the AMO, EA and SCA. Conversely, this specificity is present in the index-Rainfall WTC of the three indices above but not in rainfall WTCs corresponding to the NAO and GBI. Given that these sets of frequencies are present in the NAO and GBI groundwater WTCs, it implies that it is caused by differences between the climate indices rather than by the physical characteristics of the study sites.

Lastly, the Dripsey presents strong correlations with all the climate indices (Figure 7.6). Hence, the rainfall patterns are clearly influenced by all the indices, which is transmitted directly into the groundwater levels (Figure 7.9). As reflected in the CWTs (Figure 7.3), the groundwater levels of the Dripsey are those which better reflect the rainfall signal at the monthly scale, despite the important damping of the signal observed at a daily scale (Figure 7.4c).

7.4. Discussion and Conclusions

In this chapter, Continuous Wavelet Transforms and Wavelet Coherence have been used to analyse the relationship between rainfall, temperature and groundwater levels, and in the assessment of the influences that large scale atmospheric patterns exert on groundwater levels. Despite the large amount of information provided by this method, the difficulties to establish causality through the WTC must be kept in mind (Grinsted et al. 2004) as it constitutes the main limitations of the interpretations provided in this chapter.

The application of the WTC to daily rainfall-groundwater levels time-series, has proven useful to investigate the local infiltration and recharge processes and reveals structural differences between the catchments. More specifically, the results obtained suggest that the presence of a well-developed transition zone would dampen the rainfall signal for daily to weekly periodicities, as it constitutes a preferential pathway as has been observed in the Dripsey catchment. In this way, the transition zone would divert most of the potential recharge laterally as interflow, buffering the recharge signal in the shallow bedrock below.

The results presented in this chapter also evidence that the groundwater resources are affected by the large-scale modes of climate variability (AMO, NAO, GBI, EA and SCA).

Nevertheless, it has also been shown that each study site presents higher sensitivity to specific indices as a consequence of local rainfall variability. In addition, the local hydrogeological characteristics can significantly impact the effect of the indices by amplifying or attenuating them.

An amplification of the signal in the groundwater record can occur because of: (1) the time-scale difference between the rainfall and the recharge processes and (2) the '*memory effect*' of the aquifer system or autocorrelation of the groundwater levels (Lee and Lee 2000). However, this amplification does not occur consistently and may just be observed in boreholes where the correlation between the particular index and the rainfall are significant. On the other hand, an important attenuation of the signal can also be observed, which can occasionally lead to the complete cancellation of the signal in a specific range of frequencies. The attenuation of these frequencies cannot be linked to the damping caused by the vegetation and/or vadose zone as described in Rust et al. (2018), as this does not occur for all the indices at the same borehole. However, this phenomenon seems to be more likely to appear (but not exclusively) when there is a weak correlation between the index and the rainfall.

Wavelet Coherence has been applied in a number of previous studies (ie: Holman et al. 2011; Tremblay et al. 2011; Perez-Valdivia et al. 2012; Kuss and Gurdak 2014; Lavers et al. 2015; Velasco et al. 2017; Neves et al. 2019) to investigate the long term (annual to multiannual) impact of these indices on the groundwater resources. In this study, the unavailability of longer groundwater monitoring datasets prevented the analysis of high periodicities, which are particularly important in indices such as the AMO that show multidecadal cyclicities. In the case of the Knocktopher, the reconstruction of the earlier time series would require the application of complex reconstruction methods (i.e. wavelets or machine learning techniques) that are likely to modify the groundwater signal causing distortions in the wavelet coherence.

Holman et al. (2011) concluded that the little consistent coherence apparent for periodicities of less than 1 year demonstrates that these large-scale teleconnection indices are not drivers of seasonal variability in groundwater dynamics, which are controlled by local precipitation and evapotranspiration patterns. Nevertheless, it has been demonstrated here that the indices with a strong fingerprint, such as the AMO and the NAO, influence the seasonal groundwater levels when there is a strong signal from the teleconnection pattern. This has

important implications in terms of groundwater resources management. In the case of the AMO, an especially wet summer minimizes the seasonal depletion and stress on connected streams and dependent ecosystems. Nonetheless, this seasonal fingerprint can have particularly significant implications for the winter NAO as it can now be forecasted (Scaife et al. 2014). For instance, the exceptionally wet winter of 2015-2016 coincided with a strong winter NAO signal. In that winter, important flooding events affected UK and Ireland, where groundwater flooding also occurred. Thus, a better understanding of the relationship between the local water table dynamics with these large-scale patterns in areas susceptible to flooding, would not only improve groundwater resources management but could also play an important role in flood forecasting. Hence, further investigation between strong positive winter NAO and flooding events is required, but it is beyond the scope of this thesis and will be considered for future research lines.

The strongest NAO signal has been detected for the Mattock catchment, where an annual specificity can be observed on the second half of the time-series, when the NAO phase shifted to positive. Rather than indicating an actual annual cycle, these results suggest that the increased rainfall (and recharge) in positive NAO phases have an impact on the annual groundwater resources. Furthermore, the GBI has been found to present the same significant coherence areas as the NAO, but with opposite phase information.

The relationship between the EA and the water table is more complex because of its concomitant relationship with the NAO and the high non-stationarities of the EA during the period studied. Consequently, little consistent coherence occurs in the considered time series. Similarly, it is difficult to establish a phase-relationship with the SCA or to identify a specific seasonal fingerprint. However, an annual coherence area indicating enhanced groundwater recharge can be observed in the Mattock and the Dripsey catchments. The latter also displays a continuous band of coherence corresponding to a 2-year periodicity. Despite the importance and consistency of this area it cannot be interpreted as a cyclicity as it could be an artefact caused by the short duration of the time-series. Furthermore, it is well-known that the EA and SCA indices can modify the NAO dipole depending on their relative phase and increasing or decreasing precipitation over Ireland depending on the phase combination (Comas-Bru and Mcdermott 2014), and it has been linked with water table dynamics in Portugal (Neves et al. 2019). However, in this study it has not been possible to establish a clear and consistent relationship between indices interaction and their effect on the groundwater levels.

8. Groundwater level forecasting: Coupling Wavelet Transforms and Artificial Neural Networks

8.1 Introduction

Reliable groundwater level forecasts are essential for sustainable management of groundwater resources and, consequently, their preservation. For instance, an accurate forecast of groundwater levels (GWL) in coastal aquifers, can prevent their overexploitation and consequent salinization. Nevertheless, modelling of the water table fluctuations is particularly complex given the stochasticity of the processes involved (e.g. precipitation), uncertainties (e.g. specific yield), and the high non-linearities of the infiltration and recharge processes (see Section 7.3.2.1), and the heterogeneity of the aquifer properties.

Groundwater level modelling has been typically approached by physically-based numerical models, that represent the actual processes governing GWL dynamics (e.g. Borsi et al. 2013). However, the application of these models requires a full understanding of the conceptual model, which should include the constraints of relevant local hydrogeological features; from land use and cover to geological structure and aquifer transmissivity. Nevertheless, to build parsimonious models, significant assumptions and simplifications of the processes occurring in the subsurface need to be made. Consequently, numerical models often produce flawed results despite the good understanding of the governing laws (Sun et al. 2016). Additionally, the implementation of numerical models requires large datasets that are not always available.

In contrast, data-driven models use equations - or algorithms - to calculate a system response to input stresses without quantifying the physical properties of the system (Bair 2016). Hence, the understanding of the underlying physical mechanisms is not necessary for the implementation of the so-called *black-box* models. In recent years, there has been a rise in the use of machine-learning techniques in surface hydrology and, more recently, in hydrogeology. Data-driven modelling is an area of rapid development that has led to its application to the forecast of groundwater levels (e.g. Adamowski and Chan 2011; Chitsazan et al. 2015; Chang et al. 2016; Barzegar et al. 2017; Wunsch et al. 2018).

The most common method for data-driven models is the artificial neural networks (ANN), which can be defined as a massively parallel-distributed information-processing system that has certain performance characteristics resembling the human brain (Haykin 1999). Hence, the objective of the application of an ANN is to generalise the relationship between the input variables and the target variable (Govindaraju 2000).

There are different types of ANN depending on their internal structure. The most commonly used in hydrological sciences is the multi-layer-perceptron (MLP) approach, which has been used in a considerable number of studies to simulate groundwater levels (e.g. Coulibaly et al. 2001; Coppola et al. 2003; Adamowski and Chan 2011; Yoon et al. 2011; Taormina et al. 2012; Chitsazan et al. 2015; Khalil et al. 2015; Chang et al. 2016; Barzegar et al. 2017). These networks are composed of several layers that transmit the information only forward, i.e., from explicative variables (inputs) towards the target variable (output). However, when the system being modelled presents a high autocorrelation, as in the case of groundwater levels, this characteristic is a disadvantage. Alternatively, Nonlinear Autoregressive Networks with Exogenous inputs (NARX) can be applied instead, as the output of a given simulation step is can be used to inform the next simulation step. However, this type of ANN has been used in fewer hydrogeological studies (Izady et al. 2013; Guzman et al. 2017; Wunsch et al. 2018).

Nevertheless, the data-driven models also present considerable limitations regarding nonlinear and nonstationary processes and, in response, some hybrid modelling approaches have been developed to overcome these limitations (Rajaei et al. 2019). A clear example is the coupling of the ANN with Wavelet Transforms as a pre-processing tool of the input data. In this way, several studies use Discrete Wavelet Transforms (DWT) to decompose the time series of the explanatory variables, that are then fed into the ANN models (e.g. Adamowski and Chan 2011; Barzegar et al. 2017)

As it has been described in previous chapters, the hydrogeology of Ireland is largely characterised by fractured bedrock aquifers with limited storage capacity (Chapter 2), in which annual recharge is strongly influenced by the hydrometeorological seasonal variability (Chapter 6). Furthermore, the analysis of the rainfall-groundwater levels relationship through the application of the WTC at daily resolution has revealed the high non-linearities of the recharge processes at the study catchments (see Section 7.3.2.1). Therefore, to be able to account for the limited storage capacity - and nonlinearities - of the aquifers when forecasting the groundwater levels, a method combining wavelet transform analysis and

neural network forecasts has been applied and is presented in this chapter (Chang et al. 2016; Barzegar et al. 2017; Ebrahimi and Rajaei 2017). In this case, Maximum Overlap Discrete Wavelet Transforms (MODWT) have been used to perform a Multiresolution Analysis (MRA) and decompose the time series of the variables used as predictors into details (i.e. rainfall, temperature and PE) that are then fed into the NARX model as distinct inputs. In this way, the decomposition of the explanatory variables provides simpler input signals, which would facilitate the generalisation process for the ANN, leading to a better performance. The advantages of the input features decomposition are investigated here by comparing the performance of the NARX models when trained with decomposed and non-decomposed (raw) input time series.

Additionally, it is known that the selection of the input features affects significantly the performance of the ANN models. Therefore, in this chapter the way aggregation of the decomposed signals obtained from the MODWT affects the performance of the models is also investigated. To do so, three different aggregation criteria have been applied, and their performances are compared.

8.2 Methods

The methodology presented below is applied to model the groundwater levels at the two main study catchments; Mattock and Dripsey (see Section 3.2, Figure 3.1). More specifically, to the MK1-Shallow and DR1- Shallow boreholes for the Mattock and Dripsey respectively, 2008-2018 period as in Chapter 7. This approach enables the forecasting of monthly groundwater levels up to twelve time steps, that is one year.

8.2.1 Time Series Pre-Analysis

The selection of relevant features and minimization of redundancy is a critical *a priori* step for machine learning. First, a model as robust and realistic as possible is desired, which is usually achieved by considering all the predictors connected to the predicted variable. Second, a model with a smaller number of variables that minimizes the number of irrelevant features increases the accuracy of the predicted values and simplifies the model. Hence, the problem is similar to the one presented in classical hydrological models: simplistic models cannot represent all the physical processes, but complicated models with a large set of

parameters lead to issues of equifinality and overparameterization (Beven 2006, 2011). The objective is, therefore, to build parsimonious models that can explain the hydrological processes without being overly complicated. In machine learning and data-driven models, this is translated into finding the best set of features that can explain most of the variance without overfitting.

In this section, the pre-analysis conducted prior to the implementation of the NARX is presented: (1) the application of principal component analysis (PCA) to inform the selection of variables to be used as predictors; (2) the decomposition of the selected variables using the MODWT-MRA; and finally, the detail aggregation criteria followed to reduce the number of inputs and group them into a physically meaningful sets of inputs to account for the system properties.

8.2.1.1 Principal Component Analysis

The PCA is a multivariate statistical method, mostly used to perform an orthogonal transformation of the explanatory variables into a set of new variables (Principal Components) which are defined as being linearly uncorrelated (Jolliffe 1986, 2002). Therefore, the PCA can be used to: (i) assess and reduce the redundancy between variables or (ii) to identify possible linear relationships between variables. Here, the PCA was carried out to investigate the relationship between the hydrometeorological or explanatory variables (i.e. potential evapotranspiration, mean, maximum and minimum temperature and rainfall) and the groundwater levels (explained variable). Three components were selected so that they would explain over 90% of the variance. Hence, the PCA has not been used in its more classical application, as a dimensionality reduction tool, but to assess qualitatively the relationships between variables and inform the selection of input variables for the ANN.

The six variables included in the analysis are plotted in a 3-D chart (Figure 8.1), where the direction and length of each vector indicates how each variable contributes to the corresponding component. As can be observed, both catchments show comparable configurations without significant differences. As would be expected, maximum, minimum and mean temperature contribute to a similar extent to all the three components. In addition, the scores of these three variables are similar for all the components. However, mean temperature presents a slightly higher score for the first component - that in both cases explains over 60% of the variance - and consequently was chosen as the temperature input

variable for the ANN. Therefore, the three variables selected as inputs for the ANN are: rainfall, mean temperature and PE.

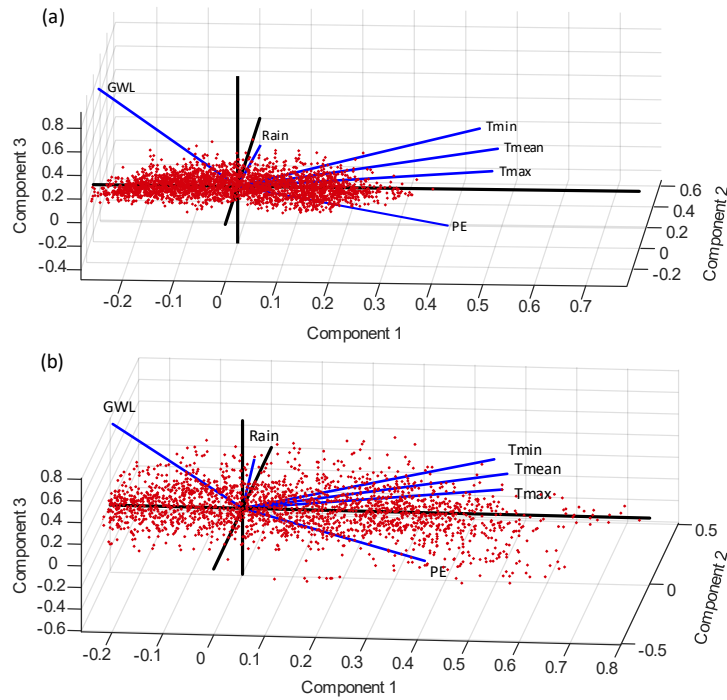


Figure 8.1: 3D projection of the input variables considered in the Principal Components space for (a) the Mattock and (b) the Dripsey. Notations: GWL: Groundwater Levels, T_{min} : minimal temperature, T_{mean} : average temperature, T_{max} : maximum temperature, PE: Potential Evapotranspiration, Rain: rainfall.

8.2.2 Discrete Wavelet Transforms

An introduction to Wavelet Transforms (WT) and their properties has been presented in Chapter 7 together with a more detailed explanation of Continuous Wavelet Transforms (CWT) and Wavelet Coherence (WTC). In this chapter, Discrete Wavelet Transforms (DWT), and their variant Maximum Overlap Discrete Wavelet Transforms (MODWT), are introduced since these mathematical tools have been used to decompose the input time series that have then been used to model GWLs.

CWTs are applied through all the possible scales and translations within a signal whereas DWTs operate on specific values. This characteristic, that distinguishes CWTs from DWTs, is also the cause of redundancy in CWTs; this redundancy stems from the fact that CWTs are calculated from the continuous shifting of a continuously scalable function over a signal and calculating the correlation between the two. Consequently, the transform functions do not

have an orthogonal basis and the resulting coefficients are highly redundant (Valens 1999). Hence, the CWTs enable us to analyse the time-frequency information contained, for example, within our rainfall or groundwater time series, but cannot be used to decompose them as the redundancy issue - together with the infinite number of wavelets and the frequent lack of analytical solutions - and this must be achieved by using DWTs.

Furthermore, in many practical applications, such as hydro(geo)logy, continuous-time signal processes are not available but rather discrete-time signals and, consequently, the time-scale domain needs to be discretized in order to apply WTs (Labat et al. 2000a). This is achieved by modifying the previous wavelet representation (Eq. 7.1) to account for the time discretization:

$$\Psi_{(j,k)}(t) = \frac{1}{\sqrt{s_0^j}} \Psi\left(\frac{t - k\tau_0 s_0^j}{s_0^j}\right) \quad (8.1)$$

where the notation corresponds to that presented in Chapter 7. Hence, Ψ represents the wavelet, j and k denote the scale and translation factors respectively, which are equivalent to s and τ factors in equation 7.1. $s_0 > 1$ is a fixed dilation step, and the translation factor τ_0 depends on the dilation step. The DWT can be then expressed as:

$$C_{j,k}(t) = \int_{-\infty}^{+\infty} x(t) \Psi_{j,k}^*(t) dt \quad (8.2)$$

where $C_{j,k}$ are the resulting coefficients, t represents time, x the time series analysed and Ψ the mother wavelet used. Typically, $s_0=2$ and $\tau_0=1$ values are chosen so that the frequency axis has a dyadic sampling (power of two), so the continuous grid is replaced by a dyadic grid (Labat et al. 2000a), which results in the orthonormality of the wavelets (basis) and the resulting coefficients (translates and dilates), as explained below.

When DWTs are applied to continuous signals this results in sets of wavelet coefficients (or translates and dilates). The process is known as wavelet series decomposition, from which it is possible to express the considered continuous signal (e.g. rainfall) as a linear combination of the coefficients obtained to reconstruct it. However, for this reconstruction of the signal to be possible, the energy of the wavelet coefficients must lie between two positive bounds, namely A and B. When this is fulfilled, the family of wavelets (or basis functions) are referred to as frames, where A and B are the bounds of such frames. In this context, two situations can occur: (1) $A = B$ and (2) $A \neq B$. In the first case, the basis is orthonormal, and the

reconstruction is possible. In the second case, the orthonormality is lost and even though the reconstruction is possible, the reconstructed wavelet will be different from the decomposed one (Valens 1999).

The ability to decompose a signal or time series into different sub-series and then reconstruct it as a linear combination of these sub-series, is the basis of Multiresolution Wavelet Analysis (MRA) (Mallat 1989). Hence, the discrete signal (x) can be decomposed into a maximum number of levels (l) depending on its length (N) according to the expression:

$$l = \text{int} [\log (N)] \quad (8.3)$$

As long as x has a dyadic length, that is if its length is a power of two, the MRA allows the decomposition of a signal into details (high frequencies) and approximations (low frequencies) for each level of decomposition (l) and scale (j) as represented in Figure 8.2.

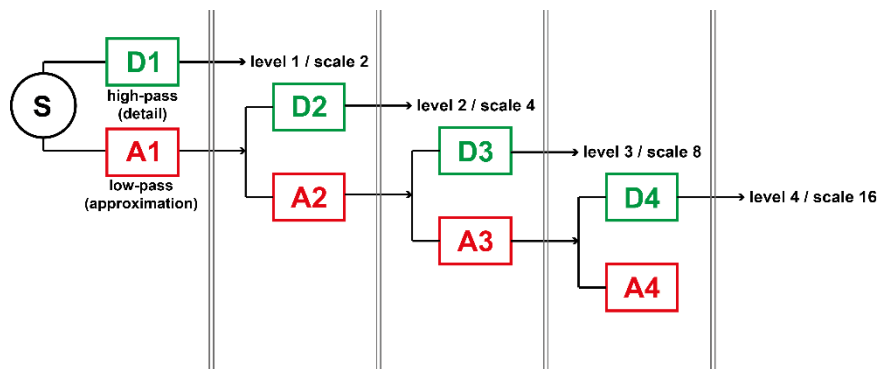


Figure 8.2: Schematic representation of the DWT-MRA decomposition of a signal into details and approximations up to four levels of decomposition, where D stands for detail, and A for Approximation. The level maximum level of decomposition possible depends on the length of the time series, in this example, $N = 4$ (Eq. 8.3).

Percival and Guttorp (1994), showed that the wavelet variance could be more efficiently estimated not by subsampling the convolution of the filters with the data, but by retaining all the values (Lark and Webster 2001). This modification of the DWT was called Maximum Overlap Discrete Wavelet Transform (MODWT), which presents certain advantages. Because the coefficients are calculated without subsampling, the new coefficients are no longer orthonormal and, therefore highly redundant (Percival and Walden 2006). Nevertheless, the MODWT is more efficient than DWT because it preserves the energy in the signal and enables avoiding border effects. Additionally, the MODWT is shift-invariant so it can be applied to time series of any sample length (Cornish et al. 2006). Hence, given a finite time series X_t of

an arbitrary length X_n , the MODWT wavelet ($\tilde{W}_{j,t}$) and scaling coefficients ($\tilde{V}_{j,t}$) can be described with equations Eq.8.4 and Eq.8.5 (Zhu et al. 2014):

$$\tilde{W}_{j,t} = \sum_{l=0}^{j-1} \check{d}_{j,l} X_{t-l \bmod N} \quad (8.4)$$

$$\tilde{V}_{j,t} = \sum_{l=0}^{j-1} \check{s}_{j,l} X_{t-l \bmod N} \quad (8.5)$$

where $L = (2^j - 1)(L - 1) + 1$, $\check{d}_{j,l}$ and $\check{s}_{j,l}$ are the corresponding wavelet and scaling filters, of l length and j decomposition levels. The MRA achieved with MODWT (MODWT-MRA) is performed in a similar way as that when based on DWTs, decomposing the signal into details and approximations for each level of decomposition and scales.

As mentioned in Chapter 7, there are a large number of mother wavelets that constitute the basis for the transformations described above. Each family of wavelets present specific characteristic and properties making them suitable for certain applications. In this study, the time-series have been decomposed up to four levels using the wavelets Daubechies 4 (also D4 or db2) (Daubechies 1992) represented in Figure 8.3. The Daubechies are frequently used in hydrological applications as their shape is appropriate to describe hydrological processes. When the “Db2” notation is used, the number two denotes the number of vanishing moments of the wavelets. In turn, these vanishing moments determine the order of the polynomial (second in this case) and, hence, the “complexity” of the signal that can be reproduced. Furthermore D4 (or Db2) were chosen as they have been used in similar studies previously (e.g. Barzegar et al. 2017; Ebrahimi and Rajaei 2017) and is in agreement with the recommendations of Quilty and Adamowski (2018).

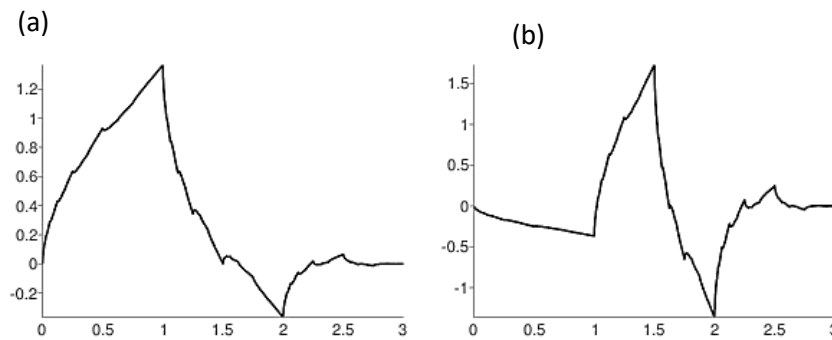


Figure 8.3: Plot of the Scaling function (a) and wavelet function (b) of the Daubechies 2 wavelet (Db,2) used in the decomposition of the time-series. Source: Wavelet Browser (<http://wavelets.pybytes.com/wavelet/db2/>)

8.2.3 Detail Aggregation Criteria

In this section, the three different approaches used to select and/or aggregate the details obtained from the MODWT decomposition are presented. The objective of this aggregation is two-fold: firstly, the details are aggregated into physically meaningful time series that may reproduce certain processes occurring within the aquifer and secondly, it reduces the number of input features. Hence, the effectiveness of the different methods is evaluated while considering the conceptual implications of the criteria considered; whereas the Bilog graphs emphasize the entire range of frequencies present in the signal, the wavelet coherence accounts for the variations in the time domain. In contrast, the stepwise regression is a linear regression that does not contribute in terms of physical meaning but selects the most relevant input features.

8.2.3.1 Bilog Graphs

Fourier Transforms take a signal or process localised on the time-domain and transform it into an equivalent signal in the frequency-domain. Thus, Fourier Transforms can be applied to perform spectral analysis of time-series, which is most useful in identifying the periodicities contained within the signal considered. The power spectrum or Fourier spectrum is defined as the square of the Fourier coefficients as a function of the frequencies of the transformed signal (Sivakumar 2016). In other words, the Fourier spectrum of a stochastic process such as rainfall, represents the energy distribution of the process depending on the frequencies present in the signal.

Fourier Spectrum has been widely applied in hydro(geo)logical sciences to analyse different processes such as streamflow or spring discharge that typically obey a power law:

$$E(\omega) \approx \omega^{-\beta} \quad (8.4)$$

where E is the energy or variance of the process, ω is the frequency and β is the spectral coefficient. As the power spectrum follows a power law, a linear regression can be fitted when it is plotted on a double-logarithmic graph (referred to as a Bilog graph hereafter). Then, the slope of the fitted line corresponds to the spectral coefficient, which can provide valuable information on the signal. For instance, for a random process, the power spectrum would oscillate around a constant value (semi-horizontal), with a slope close to 0 ($\beta \approx 0$) suggesting that none of the frequencies contained in the signal can explain more of the

variance. In the case of hydrogeological processes, the power spectrum presents a slope as they follow a statistical distribution. Thereby, changes in the slope of the fitted linear regression represent the dampening of a certain range of frequencies; in other words, a differential behaviour of the system towards high/low frequency events. In hydrogeology, this can be translated, for example, into differences in recharge mechanisms occurring within a catchment (e.g.: fast concentrated recharge vs slow diffuse recharge).

The Fourier spectrum of most hydrological and hydrogeological time series can be characterised with up to three statistical laws (Hardy and Beier 1994; Labat et al. 2000b; Dolgonosov et al. 2008; Mathevet et al. 2010). Furthermore, the cut-off frequencies indicate the different spectral domains contained within the studied signal. The method to adjust the linear law on the spectrum can be empirical (Labat et al. 2000b) or established through statistical methods (Little and Bloomfield 2010). In this study the linear adjustments were done using the “*Changepoint*” algorithm in MATLAB®, which is included within the Signal Processing Toolbox™. More specifically, this algorithm was applied so it would identify a maximum of three changing points based on the changes on mean and slope of the GWLs power spectrum. Once the significant changes have been detected, the associated cut-off frequencies are identified. Slope breaks on the Fourier power *spectrum* can represent changes on the behaviour of the aquifer system (e.g. different processes). Therefore, by aggregating the decomposed signals according to the slope breaks detected, the frequencies of the sets of inputs would be physically consistent with the different behaviours (and processes) of the GWLs. Hence, the decomposed input time-series were aggregated into the frequency bands as represented in Figure 8.4. Both spectra display distinctive behaviour for sub-annual periods (negative slope) and annual to multiannual periods (positive slope) which broadly represents that there are different processes occurring at these time scales.

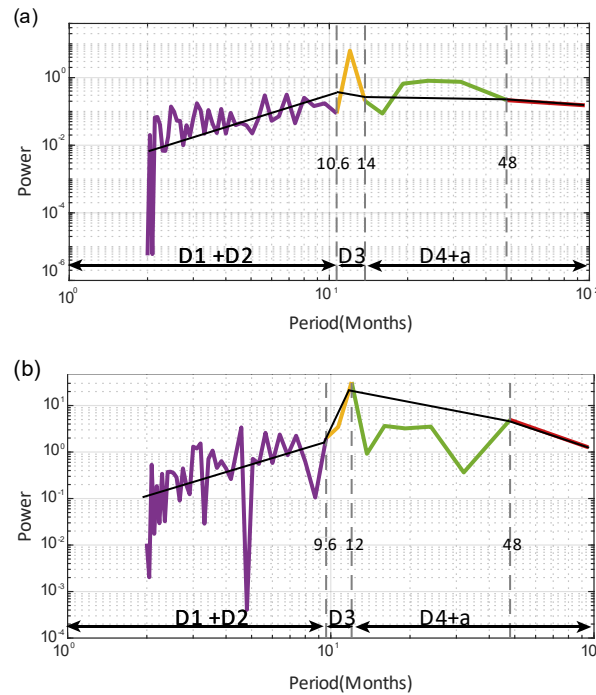


Figure 8.4: Fourier Spectrum of the groundwater levels for (a) the Mattock and (b) the Dripsey boreholes. The changes in slope detected are indicated with dashed grey lines. Changes in colour in the spectrum represent the groups of frequencies identified from the changes in slope. The black lines represent the average slopes of each segment. The groups of inputs used are noted below where “D” stands for detail and “a” for approximation.

8.2.3.2 Wavelet Coherence

As described in Chapter 7, the application of the wavelet coherence (WTC) between the rainfall and the groundwater levels at daily resolution revealed important differences in the recharge mechanisms between the Mattock and the Dripsey catchments (Section 7.3.2). Since high coherence areas represent zones of linearity between the two signals in the time-frequency space, the method can be used to determine where linear (or non-linear) modelling approaches are required (Chinarro et al. 2012). Therefore, similarly to the Fourier spectrum, wavelet coherence bands also indicate the presence of several frequency domains that, in this case, are common between the two signals. In fact, the Wavelet Coherence can be understood as a cross correlation in the time-frequency space, where the phase relationship (and lag) between the two signals is indicated by the phase arrows (see Section 7.2.1.2). For this reason, in this study, the wavelet coherence method is used to aggregate the details according to the coherence bands, their continuity in time and phase relationship (Figure 8.5).

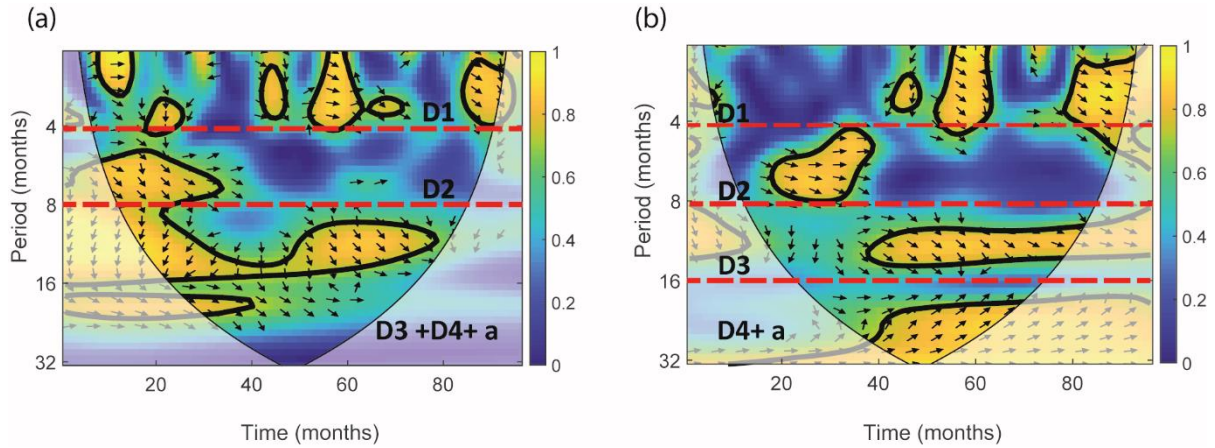


Figure 8.5: Wavelet Coherence between the rainfall and the groundwater levels for (a) the Mattock and (b) the Dripsey. The statistically significant areas (95 % significance) are delineated within the black continuous line, and the cone of influence is indicated by the shadowed area. The directional arrows indicate the phase relationship between the two phases and the colour scale represents the correlation. The red dashed lines indicate the different frequency domains identified which have been used as a detail aggregation criterion, D stands for detail and a for approximation

The idea behind this novel application of the WTC is fundamentally the same as in the Bilog Graphs, i.e., different areas of coherence - and their corresponding frequencies - represent different responses of the aquifer in relation to rainfall. Therefore, the difference between the two methods is that, instead of grouping the datasets based on ranges of frequencies, the WTC aggregation also accounts for the variations of these frequency bands in the time domain, and the phase relationship between input and output variables. In this way, the WTC-based sets of inputs would also be physically meaningful as high coherence areas at different scales represent different groundwater recharge dynamics (see Section 7.3.2.1).

8.2.3.3 Stepwise Regression

Stepwise regression is a statistical method for fitting regression models by an automatic procedure based on different algorithms (e.g. Efron 1960; Hocking 1976; Draper and Smith 1998). The regression models are built from a set of predictive variables that are iteratively added and/or removed into the model. At each step, the significance of each predictor is revised based on specific statistical tests (e.g.: The F-test) and a threshold value (e.g.: p). Furthermore, stepwise regression can also be used as an input feature selection tool (Chokmani et al. 2008; Gong et al. 2010; Peña-Arancibia et al. 2010). In this study, it is for the first time applied to select inputs from fully decomposed input signals rather than

undecomposed time series. The selected details have been fed into the stepwise algorithm to find an optimal set of predictands that have then been used as inputs for the NARX model (Table 8.1).

Table 8.1: Details selected as input features for the NARX model through the stepwise regression. D stands for detail and a for approximation.

Mattock			
	Rainfall	Tmean	PE
Details Selected	All	D1, D3, D4+a	D1, D2, D4+a
Dripsy			
	Rainfall	Tmean	PE
Details Selected	D1, D2, D4+a	D1, D2, D3	PE4+a

8.2.3.4 Summary

Rainfall, mean temperature (Tmean) and potential evapotranspiration (PE), have been selected as input variables based on the results obtained from the PCA. These three signals have then been decomposed up to four levels by applying the MODWT-MRA with Daubechies 4 wavelets, which resulted in a total of four details and the corresponding approximation for each input variable.

Given that the input feature selection is known to be of special importance when applying machine learning techniques, three different detail aggregation methods were considered: two physically based (i.e. Bilog graphs and Wavelet Coherence) and a purely statistical approach (Stepwise regression). To further investigate the effect of the number of inputs and advantages of decomposing the signals, three different sets of inputs were generated for the Bilog graphs and Wavelet Coherence method, namely: (1) all three input variables are decomposed and their details aggregated according to corresponding criteria (Bilog-All, WTC-ALL) (2) rainfall and Tmean are decomposed but PE is left undecomposed (PE-WTC), (3) only the rainfall signal is decomposed into details whereas Tmean and PE are left undecomposed (PE-T-WTC, PE-T-Bilog). Finally, another set of inputs in which the three variables are left untreated was also considered for the sake of comparison.

8.2.4 Nonlinear Autoregressive Networks with exogenous input (NARX)

As presented in the introduction section, ANN are concatenations of algorithms whose function is to recognize and generalise the underlying relationship between input and output variables through a process that mimics the way that biological brains operate (Haykin 1999). The information processing takes place within the neurones (also referred as nodes), which have input and output connection links. Each of these connection links, has an associated weight that represents the strength of the connection (Govindaraju 2000). Therefore, each neuron computes an output based on these weights and through the application of a transformation function called activation function (Dawson and Wilby 2001). Thus, this activation function determines the response of a neuron to the input signals it receives (Govindaraju 2000). In this way, neural networks are characterised by their architecture, that is, the pattern of connection between nodes, but also by how the connection weights are assigned, and the activation function (Basheer and Hajmeer 2000).

ANN can be classified in different ways, depending on some of their most relevant features such as: (i) their function (e.g. forecast, classification, clustering, etc), (ii) the internal neurons' organisation or number of layers (i.e. single, bilayer or multilayer), (iii) the direction of the information flow and propagation (i.e. feed-forward or recurrent) or (iv) the training algorithm (e.g. backpropagation).

In this study, Nonlinear Autoregressive Networks with exogenous inputs (NARX, thereafter) have been used. NARX networks are multi-layered recurrent dynamic networks based on the Autoregressive Linear model (ARX) that, coupled with ANN, enable the simulation of nonlinearities. Therefore, the main characteristic of the NARX models is the backpropagation of the outputs at each timestep, so it informs the network for the forecast of the following time step (closed loop configuration). Nevertheless, the model can be trained as a simple feed-forward network in order to simplify the process (open loop configuration) and close the system when multi-step forecasts are required (closed loop configuration) as shown in Figure 8.6. This ANN structure incorporates two activation functions, one in the hidden layer, and a second at the output layer. The first activation function is a Log-sigmoid transfer function which enables the network to generalise nonlinear processes, whereas the second one is linear transfer function.

The NARX model has been implemented using the Neural Network Toolbox™ integrated in MATLAB®. There are three main parameters to configure the architecture of the NARX model before training it: Input Delays (ID), Feedback Delays (FD) and Number of Hidden Nodes (HD). The ID can be approximated by identifying the significant lags between the predictors and the predictand. Similarly, the FD can be identified performing the lagged autocorrelation of the groundwater levels. However, there is no formal way to determine the optimal number of hidden layers that a NARX model should have, and this must be assessed by trial and error.

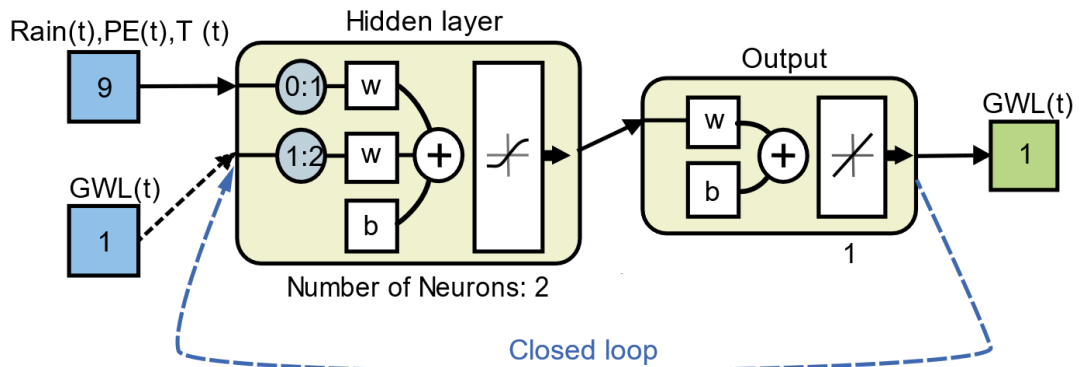


Figure 8.6: Structure of the NARX model within MATLAB with the inputs and parametrisation used in this study.

Once the NARX architecture is defined, the model can be trained. Firstly, the dataset is divided into three blocks: training, testing and validation. In this study, six years of the dataset have been used for training, one year for testing and then one year for validation. Despite this division, which may seem uneven, it should be borne in mind that the capacity of the ANN to generalise a relationship and, therefore, the transferability of the resulting model, is strongly dependant on the range of “examples” from which it has been trained. Hence, the longer the training dataset, the better transferability of the model.

As the testing is carried out automatically with the training, the validation dataset is left out of the process to ensure an unbiased estimation of the model performance. The training of the model was carried out with the Bayesian regularization backpropagation algorithm (based on the Levenberg-Marquardt optimization) to ensure a good generalisation of the NN (MacKay and Systems 1992).

The performance of the neural networks is here assessed through the Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe 1970) (see Section 6.2.4.1). In Chapter 6, this method has been complemented with the KGE. The shortcomings of using NSE on its own are related to its limited capability of accounting for the whole variability (deviation) and giving more weight to the average values. Although this is indeed an important limitation when evaluating the performance of simulated discharge, it is not so relevant in this application. In fact, given the small number of points evaluated and the purpose of this chapter, the NSE constitutes a good benchmark of the model performance.

8.3 Results

The best performances obtained for each input aggregation and study area are summarized in Table 8.2, with the corresponding configuration of the NARX model. The optimal set of parameters for each group of inputs has been evaluated through the Nash-Sutcliffe Efficiency (NSE) together with a visual assessment to ensure that the simulations reproduced the GWL dynamics plausibly. The results obtained with the full input signals (raw inputs) present NSE of 0.7 and 0.5 for the Mattock and the Dripsey respectively. The networks trained for the Mattock have generally achieved higher performances, as it could be expected given the simpler structure of the catchment. Consequently, the relationship between rainfall and groundwater levels is more linear and easier to generalise by the ANN. In contrast, the presence of a well-developed transition zone at the Dripsey dampens the signal at the shallow bedrock, which is translated into a highly nonlinear relationship between rainfall and groundwater levels for the higher frequencies as shown by the WTC (Section 7.2.1.2).

Even though the decomposition of all the variables according to the WTC (All-WTC) achieves the best performance for the Mattock catchment (NSE=0.84), it performs poorly in the Dripsey (NSE = 0.4). However, the performance obtained in the two study areas is comparable when using the PE-T-WTC aggregation, in which the PE and T signals are left non-decomposed and the rainfall signal is decomposed according to the WTC. Furthermore, the additional run with the PE-WTC grouping carried out for the Dripsey, exhibits a similar efficiency value. Hereby, the aggregations made following the WTC lead to (in most of cases) good representations of the groundwater table and improve the performance with respect to the full time-series (Figure 8.7).

Table 8.2: The NSE performance for the NARX models for each input aggregation. The parameter N_{inputs} indicates the final number of inputs for each aggregation. NSE stands for the Nash-Sutcliffe efficiency for the validation period. NH is the number of hidden nodes or neurons, and ID and FD describe the Input and Feedback delays respectively.

	Input	N_{inputs}	NSE	NH	ID	FD
Mattock	Raw inputs	3	0.7	2	0:1	1:2
	All-WTC	9	0.84	8	0:1	1:2
	PE-T-WTC	5	0.81	5	0:2	1:1
	All-Bilog	9	<0	-	-	-
	PE-T-Bilog	5	0.72	2	0:1	1:1
	Stepwise	10	0.3	3	1:2	1:1
Dripsey	Raw inputs	3	0.5	2	1:1	1:2
	All-WTC	12	0.4	2	1:4	1:1
	PE-T-WTC	6	0.82	4	1:1	1:2
	PE-WTC	9	0.79	2	1:1	1:2
	All-Bilog	9	<0	-	-	-
	PE-T-Bilog	5	0.69	3	1:1	1:2
	Stepwise	7	0.72	3	0:2	1:1

In contrast, the simulated levels obtained by applying the Bilog detail aggregation to the 3 variables (All-Bilog), present negative efficiency values in both cases. Nevertheless, their performance increases dramatically when the PE and T are not decomposed (PE-T-Bilog), with performances of 0.72 and 0.69 for the Mattock and the Dripsey respectively. Finally, the Stepwise feature selection approach presents a good efficiency for the Dripsey (NSE=0.72) but fails to simulate the GWL in the Mattock (NSE = 0.3). To summarize, the best models obtained correspond to the All-WTC aggregation for the Mattock and the PE-T-WTC for the Dripsey (Figure 8.8).

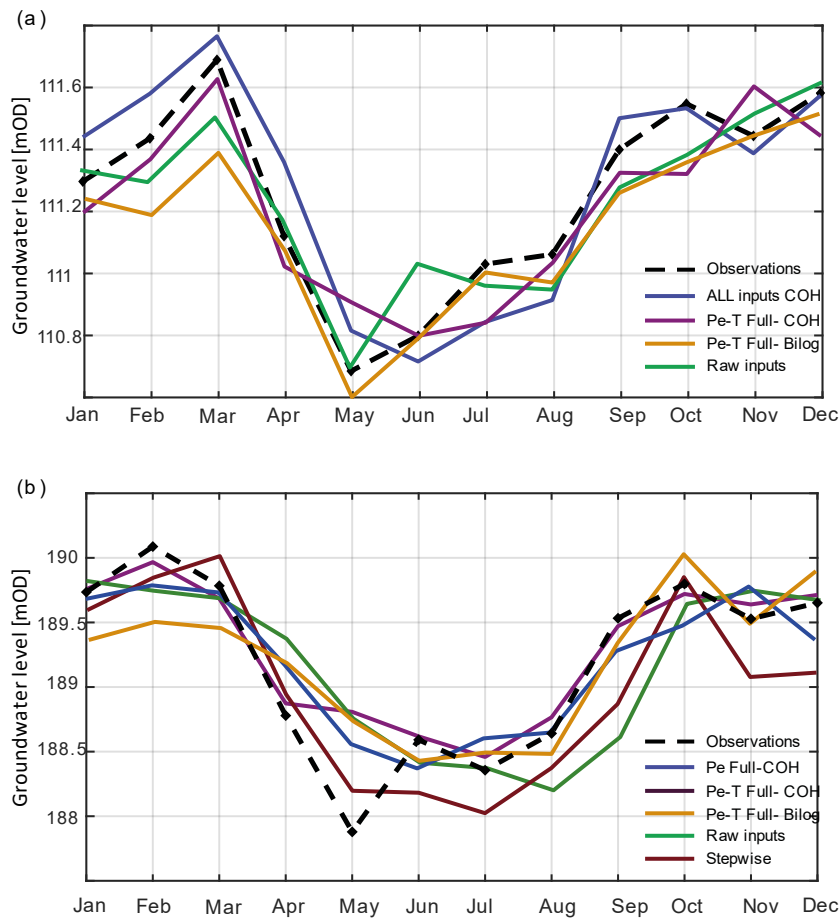
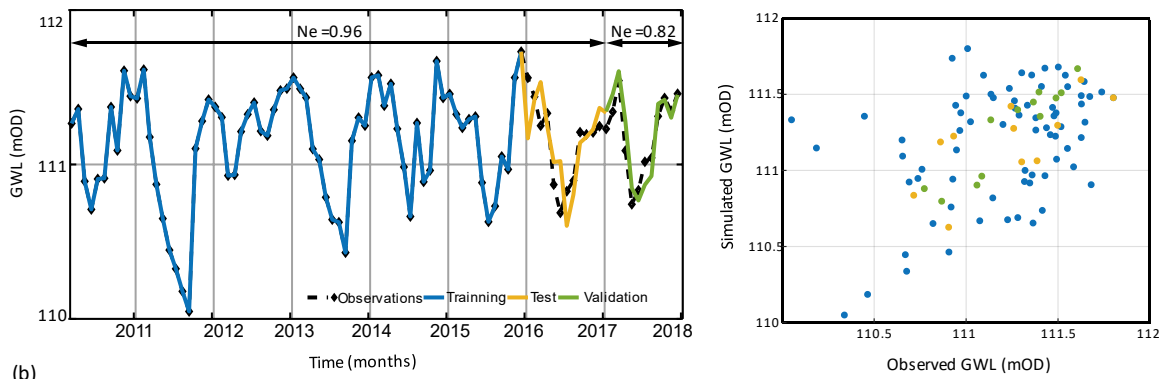


Figure 8.7: Validation period for the different input configurations for (a) the Mattock and (b) the Dripsey

On the one hand, these results suggest that the same aggregation criteria can lead to irregular performances depending on the area of application. The daily WTC (Section 7.3.1) revealed significant differences in the recharge mechanisms that operate in the two study areas. The main implication of these distinct recharge processes is a higher correlation between the rainfall and the groundwater level at the Mattock due to the absence of a well-developed transition zone. This is translated into a higher linearity, which it is easier to recognise and reproduce by the ANN. On the other hand, the disparity in performances depending on the set of inputs, highlight the importance of the input feature selection and the detail aggregation methods. This contrast is especially obvious when comparing the WTC and the Bilog aggregations: as presented above, the full decomposition according to the spectral analysis leads to negative performances in both cases and, even though the efficiency of the models increases markedly with a lower number of inputs, the performance is still significantly lower than that corresponding to the WTC grouping. The main difference between the two groupings relies on the first two details of the MODWT decomposition:

whereas in the WTC configuration the first two details are separate inputs, they are aggregated into a single input when applying the Bilog criteria. Thus, even though it is a physically meaningful separation, by summing the two higher frequency bands, the possible advantages of decomposing the input signals are lost. However, it must be kept in mind that this is most likely a consequence of working at a monthly scale, where the first two details correspond to frequency bands of 2-4 months and 3.6-9 months respectively, and that it could become an advantage when working with higher temporal resolutions.

(a)



(b)

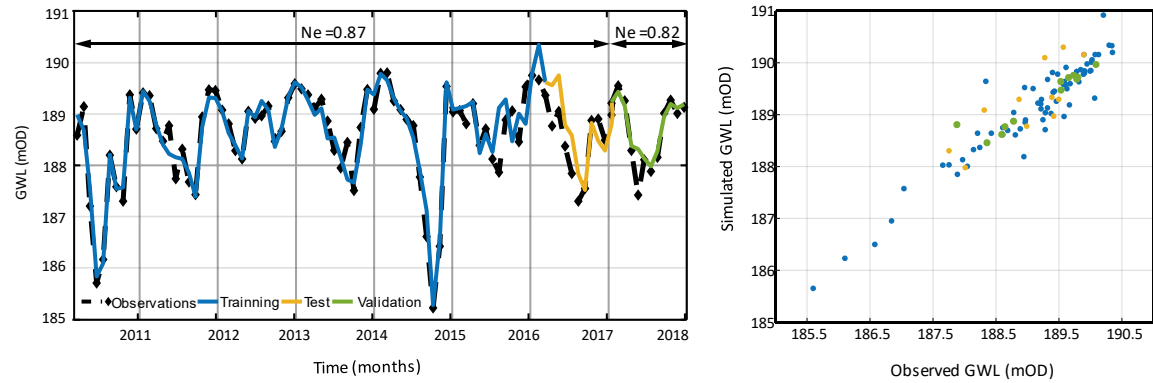


Figure 8.8: Comparison of the observed groundwater levels (black line), and the simulated levels during the training (blue), testing (yellow) and validation (green) and the corresponding scatter plots for (a) the Mattock and (b) the Dripsey with the respective best performing models: All-WTC and PE-T-WTC.

Nevertheless, if Table 8.2 is interpreted based purely on the number of inputs, it becomes clear that the lowest performances occur for models with a larger number of input features. When the number of input features is increased, there is a higher likelihood of redundancy between the input features but, most importantly, it also increases the complexity of the model. Consequently, if the number of weights is too large in comparison with the number of points in the training dataset, the network cannot be constrained leading to an overfitting of the model. In general, overfitting can occur for many reasons, but most commonly is a combination of: (1) the model is too powerful (e.g.: too many hidden nodes), (2) not enough

data, and (3) too many input features. Overfitting is easily identifiable because, generally, the model achieves a good fit during the training period but presents a poor performance during the validation. In other words, when overfitting takes place, the networks stop improving their ability to predict and start to learn from specificities and noise of the dataset, so they lose their capacity to generalize. As presented in Schittenkopf et al. (1997), the phenomenon of overfitting can also be explained in terms of Information Theory (Shannon 1948) according to which overfitting can be understood as the consequence of having too much mutual information between the inputs and the outputs or, that too much information is transmitted to the network.

8.4 Discussion and Conclusions

In this chapter, a coupled WT-NARX model has been developed to forecast monthly groundwater levels at two different locations. A preliminary analysis was conducted in order to evaluate the relevance of each of the hydrometeorological variables as predictands, as well as the relationship between rainfall and groundwater levels. Therefore, a PCA was performed to assess qualitatively the significance of each variable and inform the selection of predictands to be used in the model. Additionally, three different methods namely Bilog Graphs, Wavelet Coherence and Stepwise Regression, were applied to the decomposed predictand time-series as aggregation criteria in order to reduce the number of inputs and give a physical meaning to the model.

The results obtained demonstrate that the decomposition of the input variables into frequency bands enhances the NARX performance as long as overfitting does not occur. In other words, in most cases the coupled WT-ANN model performs better than the single NARX model. However, the choice of detail aggregation criteria has a strong control on the WT-NARX performance. For instance, the Bilog aggregations present lower performances than the WTC in all cases as the two higher frequency details are ensembled into a single input feature and consequently, the higher resolution on high frequency events is lost. Furthermore, it has also been shown that a specific aggregation method can lead to contrasting performances depending on the area of application due to local hydrogeological properties.

In this study, a number of measures to minimize the possibility of overfitting were implemented. Firstly, the training algorithm used is the so-called Bayesian regularization. This function minimizes the combinations of squared errors and weights by updating them following the Levenberg-Marquardt optimization. Secondly, the number of hidden nodes were evaluated for each model, with best results obtained in most cases with 2 to 4 nodes. Thirdly, the objective of the detail aggregation criteria was not just to give physical meaning to the detail aggregation but also to lessen the number of input features. Despite the efforts, overfitting occurred in some cases for 9 or more inputs. Although the models derived from the details grouped using WTC and the Bilog have achieved good performances, and have the advantage of being physically meaningful, their ability to lessen the number of outputs depends on the complexity of the system. In this way, when the complexity of the catchment requires a higher decomposition of the signals (such as the Dripsey) it can result in a larger number of input features that leads to overfitting and to a poor performance.

Even though the overfitting problem is well known and occurs in a large number of studies on this topic (e.g. Tetko et al. 1995; Prechelt 1998; Lawrence and Giles 2002; Srivastava et al. 2014) there is not a clear recipe for avoiding it. Piotrowski and Napiorkowski (2013) compare three methods to avoid overfitting in hydrological studies, namely early stopping, noise injection and the selection of the training algorithm. In this case, the early stopping technique is not possible to apply due to the fast training process of the NARX model for low numbers of neurons, which have been found to result in better performances. However, the Levenberg-Marquardt training algorithm was used following their recommendations. Finally, the authors also propose to inject noise to the input variables. The implementation of this method, however, is beyond the scope of this thesis but will be considered for future work as it could potentially improve the performance of the model.

The Stepwise regression based NARX models present contrasting performances for the two study areas due to overfitting. Whereas the model generated for the Dripsey catchment presents an acceptable performance ($NSE = 0.72$), the set of 10 inputs selected for the Mattock lead to a poor efficiency of the model. Although the number of predictors could have been reduced by setting a higher significance threshold in the regression model, it was not possible to know beforehand what the maximum number of inputs that can be used without leading to an overfitting of the model. The Stepwise regression is frequently used in hydrology with different applications such as building linear models (e.g. Mangin 1984; Chokmani et al. 2008), selecting predictors for models (e.g. (Barnett et al. 2009; Gong et al.

2010; Peña-Arancibia et al. 2010), and identifying time lags (e.g. Barzegar et al. 2017). However, some authors have started to question its ability to both generate robust regression models (e.g. Whittingham et al. 2006) and select input features efficiently for other models due to the intrinsic limitations of the method. Ssegane et al. (2012a, b), compared the performance of classical approaches such as PCA and Stepwise regression to newly developed techniques based on Bayesian networks that look for causal relationships between the variables. Just two out of the four techniques performed better than Stepwise regression, so the recommendation of the authors is to use more than one method in order to improve the reliability of the selection.

Lastly, the application of hybrid WT-ANN techniques in hydro(geo)logical sciences is an approach that has been developed mainly during the last decade, as the possibility of forecasting highly complex and non-linear processes (i.e. infiltration and recharge) without the need of complex physically-based models is an appealing advantage (Ebrahimi and Rajaei 2017). As a novel approach under development -which involves complex mathematical tools - different methodological approaches have been applied during the last decade without a structured methodological framework. Recently, Quilty and Adamowski (2018) pointed out the limitations of this approach as the application of DWT and MODWT-MRA present border effects that affect the performance of the model. The authors state that the MODWT-MRA provides unrealistic simulations, not applicable for real-time forecasts. Nevertheless, their results also show that this methodology achieves higher performances overall, which just decreases for the last three points simulated. Hence, even though it is acknowledged in this thesis that the application of MODWT-MRA introduces error into the model, the performances achieved are considered acceptable as the objective of this modelling exercise is not to provide real time groundwater levels forecast but a general estimation of the groundwater levels under different climate conditions. The substitution of MODWT-MRA for MODWT will be taken into account for future work and further improvement of the model.

Finally, one of the limitations of the methodology presented in this chapter is the relative short-term nature of the groundwater predictions. The decision to limit the simulation to one year was taken based on the fact that some authors have noticed that the performance of NARX models decrease with time (e.g. Wunsch et al. 2018), and most of the existing studies simulate similar time periods (e.g. Daliakopoulos et al. 2005; Lallahem et al. 2005; Adamowski and Chan 2011; Barzegar et al. 2017). The improvement of the NARX's forecasting capacity

The Impacts of Climate Change on groundwater recharge in low storativity fractured bedrock aquifers

of is out of the scope of this thesis but will be considered in the future as an enhancement of the proposed methodology.

9. Climate Change and Groundwater Recharge at Catchment scale

9.1. Introduction

Groundwater is a critical source of fresh water throughout the world as it accounts for approximately 97% of the freshwater on Earth other than the water stored in glaciers and icecaps (Shiklomanov 1998). Besides its important role as a water supply, groundwater also plays a vital role in less visible ways such as maintaining the river base flow or providing water to dependant ecosystems. However, groundwater recharge also connects the different components of the hydrological cycle, from atmospheric to subsurface, making it sensitive to both climatic and anthropogenic factors (e.g. Gurdak et al. 2009). Therefore, it is necessary to understand how contrasting climate regimes can affect the recharge processes for a better estimation of the available groundwater resources, and sustainable resources management. Moreover, it has been demonstrated that the specific characteristics of Irish hydrogeological settings could have an important control on the magnitude of the impacts of climate change at a local scale, resulting in heterogeneous impacts across the country (see Chapter 4). Hence, a good knowledge of the recharge mechanisms and hydrogeological constraints is required in order to carry out informed assessments of climate change impacts.

For this purpose, a detailed recharge characterisation involving five different methodologies was conducted for the two main study catchments. The results of this recharge calculation exercise helped constrain the recharge uncertainty within the study areas but also highlighted the limited storage capacity of these fractured aquifers (see Chapter 6). As the sensitivity analysis results suggested that this is the main governing factor in Irish fractured aquifers (see Section 4.3), to be able to account for this restricted storage capacity under future climate scenarios, a method combining wavelet transforms (WT) and nonlinear autoregressive neural networks with exogenous inputs (NARX) was implemented to forecast groundwater levels (see Chapter 8). Although the methodology implemented in Chapter 8 would be suitable for any hydrogeological setting, it is of particular interest in this context where the classical model approaches could not represent the complexity of the recharge processes.

The possible impacts of climate change on (ground)water resources are conventionally assessed through a ‘top-down’ approach (Wilby 2005) which consists of using the downscaled outputs of the General Circulation Models (GCMs) as inputs for hydro(geo)logical models. Despite being the most common approach, it is not exempt of shortcomings. Firstly, there is an inherent uncertainty at each stage of the modelling process which propagates and is further enhanced at each subsequent step, resulting in what some authors have described as a cascade of uncertainty (e.g. Bastola et al. 2012). Secondly, in recent years, the suitability of the GCMs has been questioned as it has been shown that different GCMs (and consequently the corresponding downscaled RCMs) are interdependent and share flaws (Knutti et al. 2013). Furthermore, it has also been demonstrated that the GCMs are unable to reproduce the past climate (Anagnostopoulos et al. 2010), specific local behaviours such as storminess (Shepherd 2016), or even large scale-circulation patterns (Stephenson et al. 2006; Stoner et al. 2009; Furtado et al. 2011; Lapp et al. 2012) as discussed in Chapter 7.

In the light of all these problems, some authors have proposed alternative approaches based on stress-testing (sensitivity analysis) the systems (e.g. Wilby and Dessai 2010; Hazeleger et al. 2015; Shepherd et al. 2018). However, even when the uncertainty of the climate projections is removed from the equation, the inherent structural uncertainties of the hydrological model persist through equifinality issues, and the assumption of parametrization stationarity (Broderick et al. 2016).

In this chapter, the possible impacts of climate change on fractured Irish aquifers are assessed with two different approaches for the two main study catchments (i.e. Mattock and Dripsey). On one hand, a ‘top-down’ approach such as that described above, is carried out through the application of the NAM rainfall-runoff model, which had been already implemented in the two study areas as a part of the recharge characterisation (see Section 6.2.4). Given the limitations described previously, the results of this approach are interpreted as a statistical characterisation of the possible future conditions used to provide an order of magnitude of the possible long-term changes on baseflow. On the other hand, the best performing WT-NARX models obtained in Chapter 8, are applied here to evaluate the possible changes on groundwater levels (GWLs). These models are first forced with climate projections in a slightly different ‘top-down’ approach. Furthermore, the results of Chapter 7 have shown that the seasonality of the GWLs is affected by the natural climate variability. In order to investigate further the sensitivity of the groundwater resources to changes in rainfall occurrence and seasonality, the WT-NARX models have also been forced with

synthetic rainfall series to provide annual GWL estimations under different climate conditions. These precipitation series have been modified with the SDSM-DC software (Wilby et al. 2002) to represent changes in wet-days occurrence (occurrence, hereinafter) and overall seasonality.

Therefore, the main objective of this chapter is to provide an impact assessment for the study catchments informed by the results of the previous chapters. Moreover, as the artificial neural networks have not yet been applied for this purpose, this chapter also aims to evaluate the suitability of this methodology for groundwater impact assessment.

9.2. Methods

9.2.1. Climate Change Modelling

9.2.1.1. *Climate Projections (RCMs)*

The use of General Circulation Models (GCMs) and Regional Circulation Models (RCMs) is the most widespread approach to simulate anthropogenic climate variability, and conduct climate change impact assessments (See Section 2.3.1). These numerical models provide the spatial and temporal evolution of the atmospheric processes depending on the selected initial and boundary conditions. These boundary conditions have been classically set by the Emission Scenarios that were defined by the Intergovernmental Panel on Climate Change (IPCC) in their second report assessment (Stone 1997), which represented a range of plausible socioeconomic scenarios including environmental policies and technological development.

In the fourth IPCC report (2013), these socioeconomic scenarios were substituted with Representative Concentration Pathways (RCPs) which represent the trajectory of the concentration of greenhouse gases consistent with a range of plausible anthropogenic emissions (Figure 9.1). According to IPCC, all the RCPs share a set of historical emissions data to initialize the assessment models. There is a total of four RCPs namely 2.6, 4.5, 6 and 8.5 from less to more conservative, where the numbers refer to radiative forcings (global energy imbalances), measured in watts per square metre, by the year 2100. (Table 9.1).

Table 9.1: Description of the four RCPs. Modified from IPCC, 2013.

DESCRIPTION	
RCP 8.5	Rising radiative forcing pathway leading to 8.5 W/m2 in 2100.
RCP 6	Stabilization without overshoot pathway to 6 W/m2 at stabilization after 2100
RCP 4.5	Stabilization without overshoot pathway to 4.5 W/m2 at stabilization after 2100
RCP 2.6	Peak in radiative forcing at ~ 3 W/m2 before 2100 and decline

However, these models reflect the evolution of the greenhouse gases concentration and not their emissions and, consequently, even though they are informed by the socioeconomic context they do not represent it directly. In fact, the former emission scenarios have been substituted with the so-called narratives or storylines.

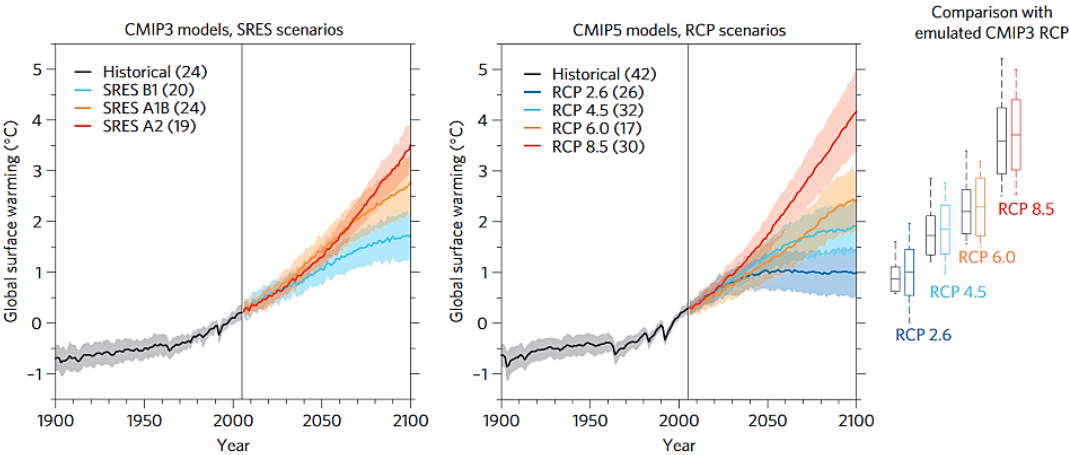


Figure 9.1: Global temperature change (standard deviation as shading) relative to 1986–2005 for the SRES scenarios run by CMIP3 and the RCP scenarios run by CMIP5. The number of models is given in brackets. The box plots (mean, standard deviation, and minimum to maximum range) are given for 2080–2099 for CMIP5 (colours) and for the MAGICC model calibrated to 19 CMIP3 models (black), both running the RCP scenarios. Source: Knutti et al., (2013)

The climate projections used in this thesis have been provided by ICHEC/EPA, and consist of five different Regional Circulation Models (RCMs) downscaled dynamically by the application of the COSMO-CLM model with a resulting resolution of 4 km. Each model presents a control or historical period (1975-2006) and a “future” period from 2006 to 2100 for which there are two representative concentration pathways: RCP 4.5 and RCP 8.5. The time series corresponding to the “future” have been subdivided into three periods for better clarity and better interpretation of the results. The periods considered are P1 (2006-2040), P2 (2040-2070) and P3 (2070-2100).

The projections provided include rainfall time series as well as maximum and minimum temperatures at daily resolution. The potential evapotranspiration (PE) data required as an input for both the NAM and WT-NARX models, has been calculated through the relatively simple Hargreaves formula (see Chapter 5) rather than with the Penman-Monteith equation. Indeed, the latter method was discarded as it was considered that using the variables required to calculate the PE (e.g. wind speed, air moisture content) would add significant uncertainty to the calculations, as the projection of these variables is less robust than for temperature (see Section 2.3.1). Finally, the daily mean temperature has been calculated with a simple mean between maximum and minimum temperatures.

During the last few decades, it has been a common practice to apply a bias correction to the downscaled RCMs in order increase their resolution and be able to use them as inputs for hydro(geo)logical models. Nevertheless, it has been demonstrated that the choice of the bias correction method has an impact on the results which is as large as the choice of the selected climate model (IPCC et al. 2013). Furthermore, the bias corrected data can alter the signal of the change for specific locations and months (Hagemann et al. 2011). For these reasons, no bias correction method has been applied for this study at the expense of introducing a certain degree of error, but in pursuit of reducing uncertainty. Hence, the changes detected in the results are measured in comparison to the corresponding historical period, and the error introduced by the projections is evaluated below.

Figure 9.2 shows the observed rainfall and mean temperature annual cycles over the historical period (1976-2006) for the two study catchments (black), as well as the corresponding effective rainfall in comparison to the annual cycles calculated from the climate models (grey). These annual cycles represent the average monthly value of each variable over the period considered, based on the meteorological data obtained from the synoptic stations in the case of the observations (see Section 3.2), and the climate models for the simulations. The hydrologically effective rainfall is calculated from the soil moisture budget as described in Chapter 5.

The temperature annual cycles present a characteristic bell shape centred on the summer months (Figure 9.2a, d). The cycles calculated from the climate models underestimate the mean temperature in both catchments, with this disparity being particularly accentuated for the colder months. Furthermore, it appears that the observed annual cycle for the Mattock catchment is slightly shifted in time, so the “bell” is centred at the end of summer and

beginning of autumn. The cycles obtained from the climate models, however, do not reproduce this seasonal shift.

In contrast, in the case of both rainfall and effective rainfall, the annual cycles corresponding to the observations fall in the middle of the range of values obtained from the climate projections, without important shifts in the seasonality. Nevertheless, it becomes obvious when comparing the three variables, that the rainfall projections present a significantly larger spread than the simulated mean temperature. As presented in Chapter 2, this is because the projections of certain variables are more robust than others. Hence, temperature projections can be estimated more accurately than rainfall as the latter is a conditional process and so both its occurrence and intensity need to be predicted. Therefore, temperature simulations or projections are more robust and present a lower inherent uncertainty.

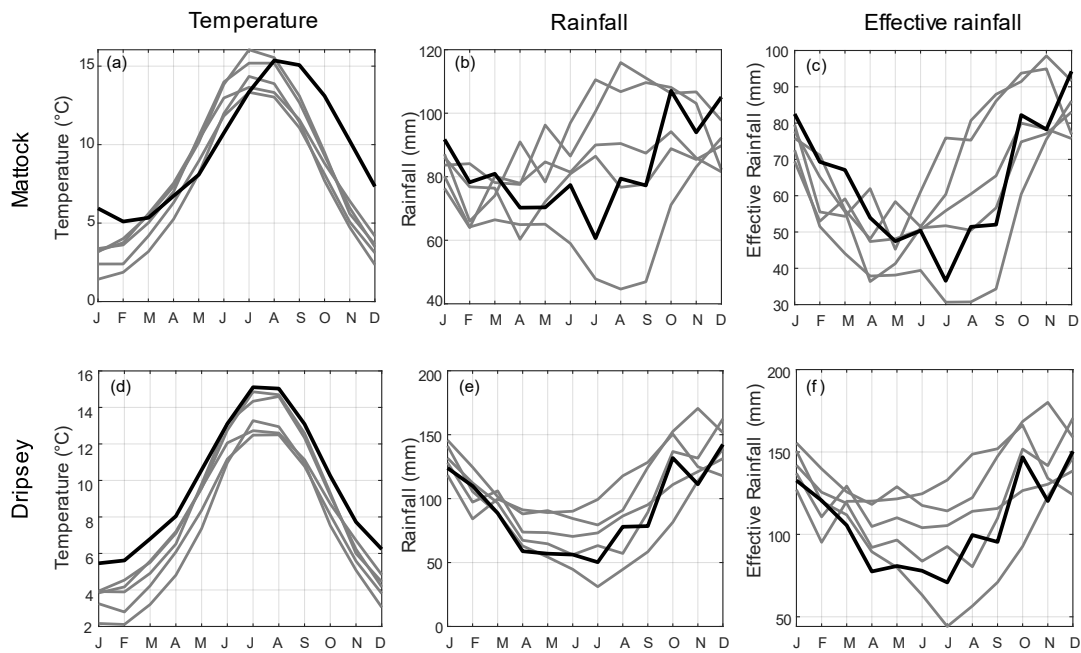


Figure 9.2: Annual cycles of the mean daily temperature (first column), monthly rainfall (middle column) and effective rainfall (last column), calculated from observed data (black) and climate models (grey) for the Mattock (first row) and the Dripsey (second row) over the historical period (1976-2006).

Furthermore, the spread observed in the rainfall (Figure 9.2b, e) is then transmitted and enhanced in the effective rainfall projections (Figure 9.2c, f) even though PE has been estimated through a temperature-based method such as Hargreaves equation. This constitutes a clear example of uncertainty propagation through calculations, even though only relatively simple calculations have been performed to this point. Further analysis of the

bias present at the climate models has been performed through the comparison of the CWTs of each variable and this is presented in APPENDIX B.

9.2.1.2. *Synthetic time-series (SDSM-DC)*

The Statistical Downscaling Method Decision Centric (SDSM-DC) software (Wilby et al. 2002, 2014) used to modify the hydrometeorological variables for the sensitivity analysis in Chapter 4 (Section 4.3) is applied here in a similar way. Hence, the precipitation time-series used in the training and validation of the WT-NARX were averaged into monthly values to represent the mean conditions of the last decade and modified according to the ranges anticipated by the climate projections and reported by the IPCC (IPCC et al. 2013). In this way, the precipitation series have been modified to represent changes in wet-days occurrence (occurrence, hereinafter) and overall seasonality.

The simulation of increased (decreased) rainfall occurrence has been performed by altering the general percentage of occurrence of wet-days, where a wet-day is considered as a day when rainfall is 0.1 mm or higher. The addition and removal process of rain days was done by a stochastic forcing, which is based on the existing likelihood of events in each month. In this way, wetter months have greater chance to get a rainy day added and vice versa. Eight new scenarios were generated: four in which wet-day occurrence was incremented from 5 to 20% at 5% intervals, and four more in which the occurrence was reduced by the same percentages (Figure 9.3a, b).

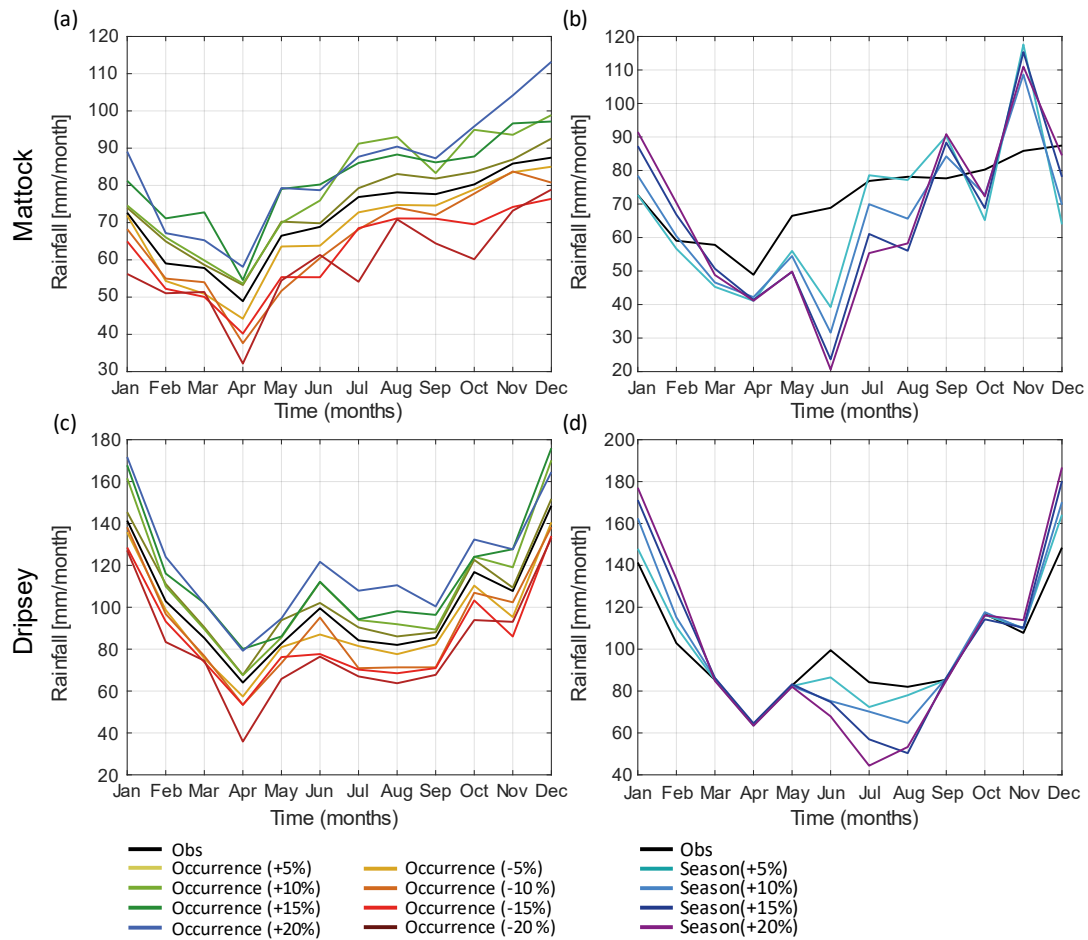


Figure 9.3: Modified rainfall series used as inputs for the WT-NARX models, simulating changes in occurrence (first column) and seasonality (second column) for the Mattock (upper row) and the Dripsey (lower row).

The alteration of the rainfall seasonality was done in a similar manner to that presented above for rainfall intensity: first, the monthly percentage of wet days is calculated, and the annual averages are fixed. Then, the number of wet days for the winter months (December, January and February) are increased, whereas rainfall events are reduced for the summer months (June, July and August), while the number of wet days are fixed for the remainder of the months in order to accentuate the seasonal effect. The precipitation time series have been modified to simulate an enhancement of its seasonality from 5 to 20% at 5 % intervals, generating a total of four additional scenarios (Figure 9.3c, d)

9.2.2. Hydrogeological Modelling

The climate projections and the synthetic time-series have been used to force two hydrogeological models in order to simulate the possible effects of climate variability in the study catchments: (1) The NAM rainfall-runoff model (See Section 6.2.4) and (2) the WT-

NARX model developed in Chapter 8 (Section 8.2.4). The general methodology used in this chapter is represented in Figure 9.4.

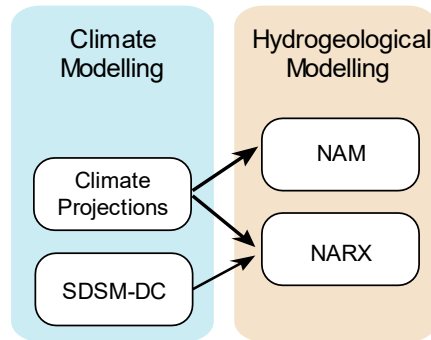


Figure 9.4: Schematic representation of the methodology followed.

The NAM rainfall-runoff model is here forced with the set of climate projections to perform long-term simulations of the possible impacts of climate change on the groundwater resources. A total of 10 permutations (5 models and 2 RCPs for each model) representing future baseflow conditions are obtained; however, the uncertainties associated with this approach must be kept in mind. The objective of applying this method is, therefore, to obtain a statistical characterisation of future baseflow conditions. In this case, the climate projections have been used at daily time-steps, and the results are then aggregated into months, seasons or years for better clarity in the interpretation. In this study, no bias correction method has been applied. Therefore, the variation simulated by each RCM and RCP is measured by comparison to the historical period (1960-2006) of the corresponding RCM. Given that the synthetic time series have been generated based on the range of change forecasted by climate projections, the NAM model has not been forced with these time series resulting from the SDSM as the results would have fallen in the range of conditions already represented by the climate projections and it would not have provided new information.

The best performing WT-NARX models trained for each catchment in Chapter 8 are used here to generate future scenarios of groundwater level by forcing these models with climate projections and modified time-series. Hence, the *All-WTC* and *PE-T-WTC* models are used for the Mattock and the Dripsey respectively (see Sections 8.3 and Table 8.2). However, the impact assessment conducted with the WT-NARX model is constrained by the length of the forecast given that, at this stage, the WT-NARX model can only simulate groundwater levels at monthly resolution for one year (i.e. twelve time-steps). Consequently, to use the climate projections as an input for this model, the monthly average value of the input variables is calculated over the four periods considered namely Historical (1960-2005), P1 (2006-2040),

P2 (2040-2070) and P3 (2070-2100). In this way, a synthetic year representing the average conditions of rainfall, PE and mean temperature is generated based on the climate projections. Then, these values are decomposed into frequency bands (or details) with the MODWT as described in Chapter 8, according to the input requirements for each WT-NARX model (Table 9.2).

Table 9.2: WT-NARX model used for each catchment (model), number of inputs (N_{inputs}) and corresponding detail aggregation. D stands for detail and a for approximation.

	Model	N_{inputs}	Rain _{inputs}	PE _{inputs}	Tmean _{inputs}
Mattock	All-WTC	9	D1; D2; D3 +D4 +a	D1; D2; D3 +D4 +a	D1; D2; D3 +D4 +a
Dripsey	PE-T-WTC	6	D1; D2; D3; D4 +a	Not decomposed	Not decomposed

In a similar way, the time-series used to train and validate the WT-NARX models have been averaged by months to represent the conditions within the catchment in the last decade. Then, these averaged values of the input variables are modified through the SDSM-DC to simulate increased (reduced) rainfall occurrence as well as enhanced seasonality. These synthetic time-series are finally decomposed and fed into the models.

This approach - in contrast to the more classical method of forcing a rainfall-runoff model with climate projections - does not aim to provide a range of likely groundwater levels but rather to assess qualitatively the vulnerability of groundwater resources to the anticipated climate variability, and evaluate the suitability of the WT-NARX models for this purpose as they have never been applied in this way before.

9.3. Results

9.3.1. NAM

The NAM rainfall-runoff model was initially forced with the historical period data of the five climate models in order to establish a baseline, to which the future projections could then be compared. Table 9.3 synthesizes the results obtained for simulated discharge and baseflow index (BFI) for the two study catchments. The values presented in the table diverge significantly from the values presented in previous chapters (see Chapter 6). The differences

are particularly important in the case of the Mattock catchment where both discharge and BFI are notably overestimated in comparison to the results presented in Chapter 6 (see Section 6.3.3 and Section 6.3.4) and previous studies of this catchment (Archbold et al. 2013; O'Brien et al. 2013). In contrast, the values obtained for the Dripsey underestimate slightly the discharge and BFI but they are still within a plausible range when compared to previous results (see Section 6.3.3 and Section 6.3.4). These discrepancies are most likely to stem from the inherent structural uncertainty of the model (present in all rainfall-runoff models) which, in the case of the Mattock, could be accentuated by the short calibration period due to the lack of available data at high temporal resolution. Therefore, the results obtained from the future periods presented below are expressed as a percentage of change with respect to the corresponding historical period.

Table 9.3: Maximum, Minimum and Mean simulated discharge (Q_{sim}) in mm/y and corresponding Baseflow Index (BFI) calculated for the historical period (1975-2006) for the two study catchments. The mean simulated discharge and BFI during the NAM calibration are also included for better comparison.

Mattock						
Q_{sim} (mm/y)				BFI (%)		
Calibration	359			17.4		
Model	Maximum	Minimum	Mean	Maximum	Minimum	Mean
CNRM	630	259	444	48	20	31
EC-EARTH	579	218	403	56	56	35
HadGem2	381	118	244	60	20	40
Miroc5	797	221	556	43	23	34
MPI	895	399	596	39	26	32
Dripsey						
Q_{sim} (mm/y)				BFI (%)		
Calibration	774			31		
Model	Maximum	Minimum	Mean	Maximum	Minimum	Mean
CNRM	1155	543	858	20	12	16
EC-EARTH	1007	596	840	21	16	18
HadGem2	880	414	630	24	17	20
Miroc5	880	436	641	23	16	21
MPI	1553	616	981	21	13	16

Figure 9.5 shows the average monthly baseflow index change, expressed as a percentage, for each period where the grey lines represent the baseflow change calculated from each climate model and the blue line the corresponding mean. The outputs corresponding for the Mattock show a similar behaviour for the three periods, where the mean change in baseflow index ranges from 0 to 50 %, with the higher increase occurring from August to November as some of the models show a BFI rise of up to 200 %. This characteristic can be identified in the annual cycles of the rainfall an effective rainfall of the historical period represented in Figure 9.2, and it exemplifies how the particularities of a given model can affect the impact assessment.

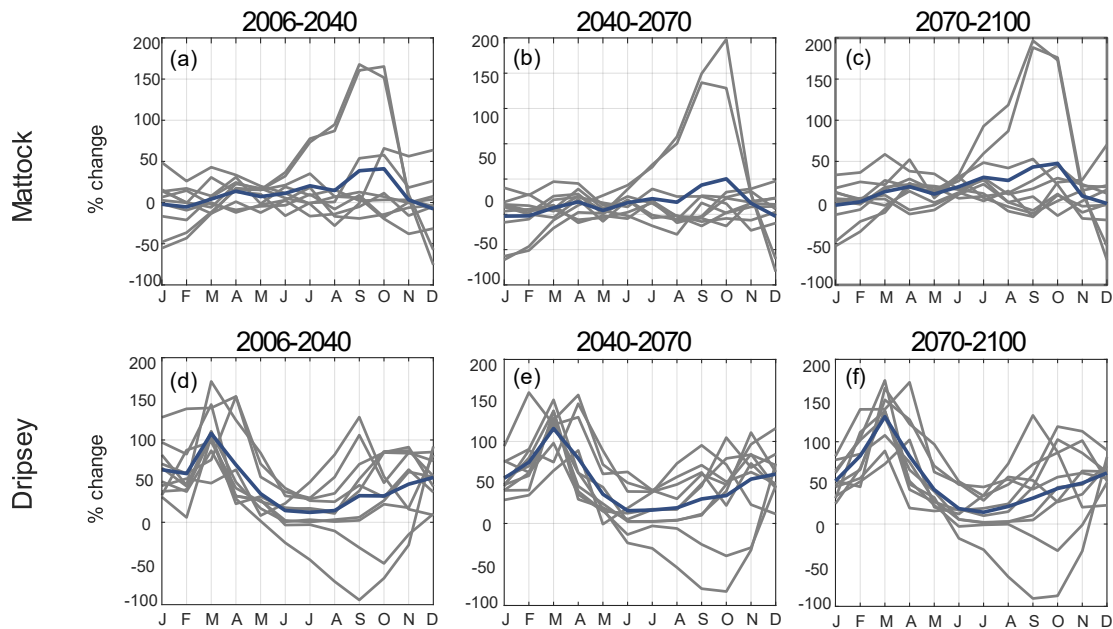


Figure 9.5: Monthly change in baseflow expressed as a percentage for each climate projection (grey) and the corresponding mean (dark blue) and its evolution during the three considered future periods; P1 (2006-2040) in the first column, P2(2040-2070) in the second column and P3 (2070-2100) at the last column, for the Mattock (first row) and the Dripsey (second row).

The range of mean BFI change observed for the Dripsey is similar to the Mattock as it varies from 5 to 65 %. Nevertheless, the results suggest an increased BFI for winter and spring with a maximum difference achieved in March, whereas lower changes are estimated for the summer months. Interestingly, each catchment present little variation between the three projection periods. This can be attributed to the fact that the results are expressed as baseflow index, that is, as the percentage of the total discharge, which is controlled by the parametrisation of the model, to represent the characteristics of the catchments.

A detailed estimation of the BFI estimated change is shown in Figure 9.6. The boxplot represents, like the previous annual cycles, the range of change at a monthly resolution. In this case, the central mark indicates the median, while the bottom and top edges of the boxes indicate the 25th and 75th percentiles, respectively. The whiskers represent the extreme data points. The first column represents the temporal evolution of these monthly changes for the Mattock. The spread in the monthly estimations decreases significantly after the first period (P1) as it is represented for shorter boxes. Overall, the results suggest an increase in the BFI, which could be particularly important for spring and autumn. The general (median) percentage of change is lower than 25%. The results show a larger change during the two first periods up to 30 % for October in the first period (2006-2040). In contrast, the results obtained by the third period (2070-2100) show an increase lower than 20 % for all the months with exception of October (25 %) .

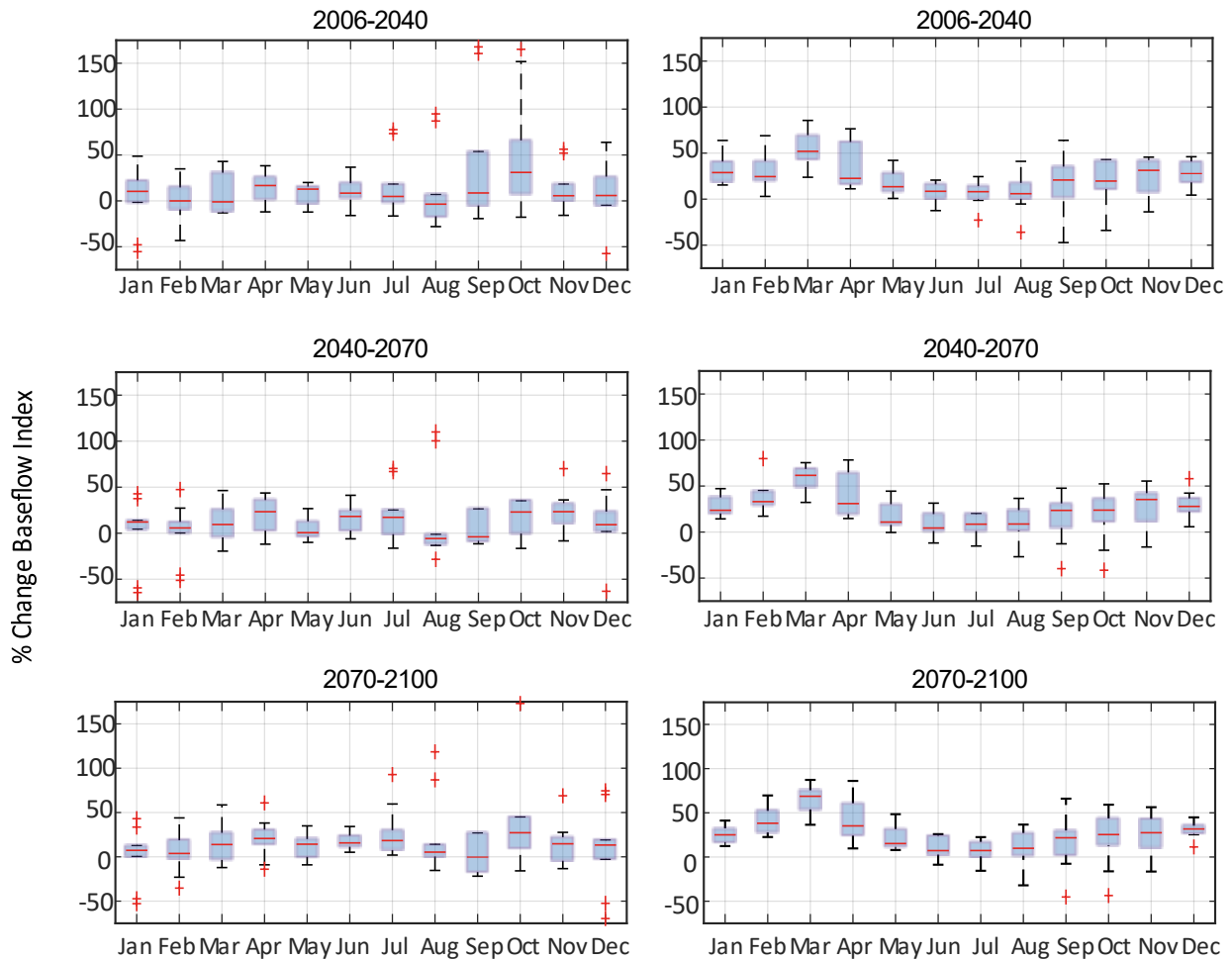


Figure 9.6: Percentage of change of the BFI for the Mattock (first column) and the Dripsey (second column) for the three future periods. The limits of the boxes represent the 25th and 75th percentiles, whereas the red line indicates the median (50th percentile). The extreme values (outliers) are represented by the red crosses.

In the case of the Dripsey, the differences between months is more acute but the spread in the monthly estimation does not vary significantly between periods. The results would indicate an important rise of the spring and autumn BFI which exceeds reaches up to 70% in March, whereas the median change for the drier months (May to September) is the lowest with values of the order of 5-20%.

Considering the baseflow range of estimations obtained in Chapter 6 through the application of the Eckhardt filter (see Section 6.3.3), and the NAM itself (see Section 6.3.4) an increase of 25% in the Mattock would be translated into a BFI of about 22% which falls in the range of BFI calculated through the baseflow separation and is considered plausible. In the case of the Dripsey, the range of changes forecasted are significantly higher. Considering the results of

Chapter 6 – and accounting for the uncertainty of the recharge estimations – it is considered that the maximum plausible BFI is 40% which corresponds to a net change of 35 %. Therefore, these results are evidencing the issues on model transferability. These issues are caused by the contrasting climate characteristics between the calibration (and validation) periods and the simulations, together with the assumption of the stationarity of the parameters.

Nevertheless, as the baseflow index represents a percentage of the total discharge, to understand the observed changes, these results need to be compared with the net change of the river discharge (Figure 9.7). The results obtained for the Mattock show an overall increase on the river discharge up to 25 % during the first period (2006-2040). Most of the months present a median net change between 5-10 % with just Jun presenting a slight decrease (-5 %) and August displaying the higher increase (+25 %). The results obtained for the 2040-2070 (P2) are very similar, with the only relevant change being that a change of signal for the month of March that, in this case, shows a 5% decrease on the river discharge. It is in the last period (P3) where the largest changes are detected; all the months show an increase on the simulated discharge between 5 and 30%, with the lowest increase being for the months of March and June and the highest increase being in January. Hence, the general increased observed previously for the BFI would be a consequence of the increase on discharge, with a lower change for the summer months, and a maximum increase for winter and autumn, which is consistent with the maximum changes observed in discharge. Nevertheless, it must be noticed that the baseflow index changes present a higher spread.

The discharge net changes obtained for the Dripsey present a similar range of variation (-10 to +25%) with slight differences: During the first period (2006-2040), most of the months presents a median increase between 5-10% with the exception of June that shows a decrease of about 10 % . In the second period (2040-2070), there is a higher range of increase (10-20%) for the majority of the months, but there is a decrease of discharge from July to September of about 10%, and March (5%). Finally, the results indicate that, during the 2070-2100 period, a further enhancement of the river discharge would occur being higher for November and December (25%) and lower for September (less than 5%) whereas there is a decrease for April and June (-10%). Overall, the changes detected in the river discharge are directly reflected on the baseflow index. The higher changes in BFI correspond to the largest increases on the simulated discharge.



Figure 9.7: Percentage of change of the river discharge for the Mattock (first column) and the Dripsey (second column) for the three future periods. The limits of the boxes represent the 25th and 75th percentiles, whereas the red line indicates the median (50th percentile). The extreme values (outliers) are represented by the red crosses.

To explore further the seasonal component of the changes in the baseflow, the baseflow time series have been divided in the four seasons: Winter (DJF), Spring (MAM), Summer (JJA) and Autumn (SON). Then, these series have been denoised (LOESS) and normalised against the average seasonal values in order to detect possible trends (Figure 9.8). A smooth upwards trend can be appreciated for both winter series, as well as for the spring baseflow in the case of the Mattock, and autumn for the Dripsey.

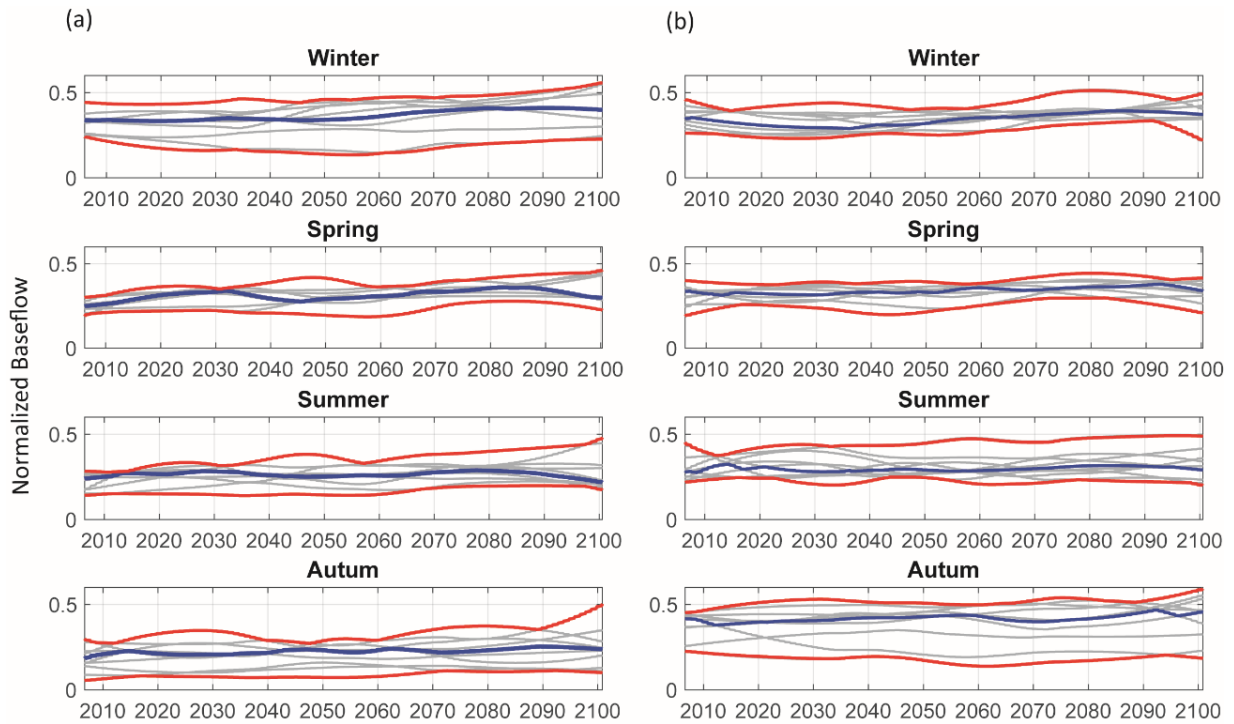


Figure 9.8: Temporal evolution of the seasonal baseflow for (a) the Mattock and (b) the Dripsey. The baseflow time series are plotted detrended and normalized (grey). The upper and lower red lines represent the 95th and 5th percentiles, whereas the dark blue line corresponds to the median.

Given the fact that climate change is expected to intensify the hydrological cycle by an enhancement of the extreme events, the probability of occurrence of maximum and minimum baseflows has been calculated using the simulations obtained by forcing the NAM model with the climate projections (Figure 9.9). The winter probability plots suggest, in general, higher maximum and minimum baseflow values with respect to the historical periods in both catchments. The signal for the summer plots, however, is not clear as there are more discrepancies between the different models and, in some cases, the signal changes from high to low probabilities. The maximum summer baseflows for the Mattock (Figure 9.9e) have a similar behaviour to what is observed for the winter extremes. Nevertheless, in the case of the Dripsey, the differences between probabilities is very narrow between different models, and between different periods for the same model. Overall, the high probability values (lower monthly baseflow) are more likely to be exceeded by the historical periods, however for low exceedance probability values (higher baseflow) the opposite is the

case. Finally, the minimum summer baseflows also present mixed signals but the results show predominantly a reduction in minimum summer baseflow.

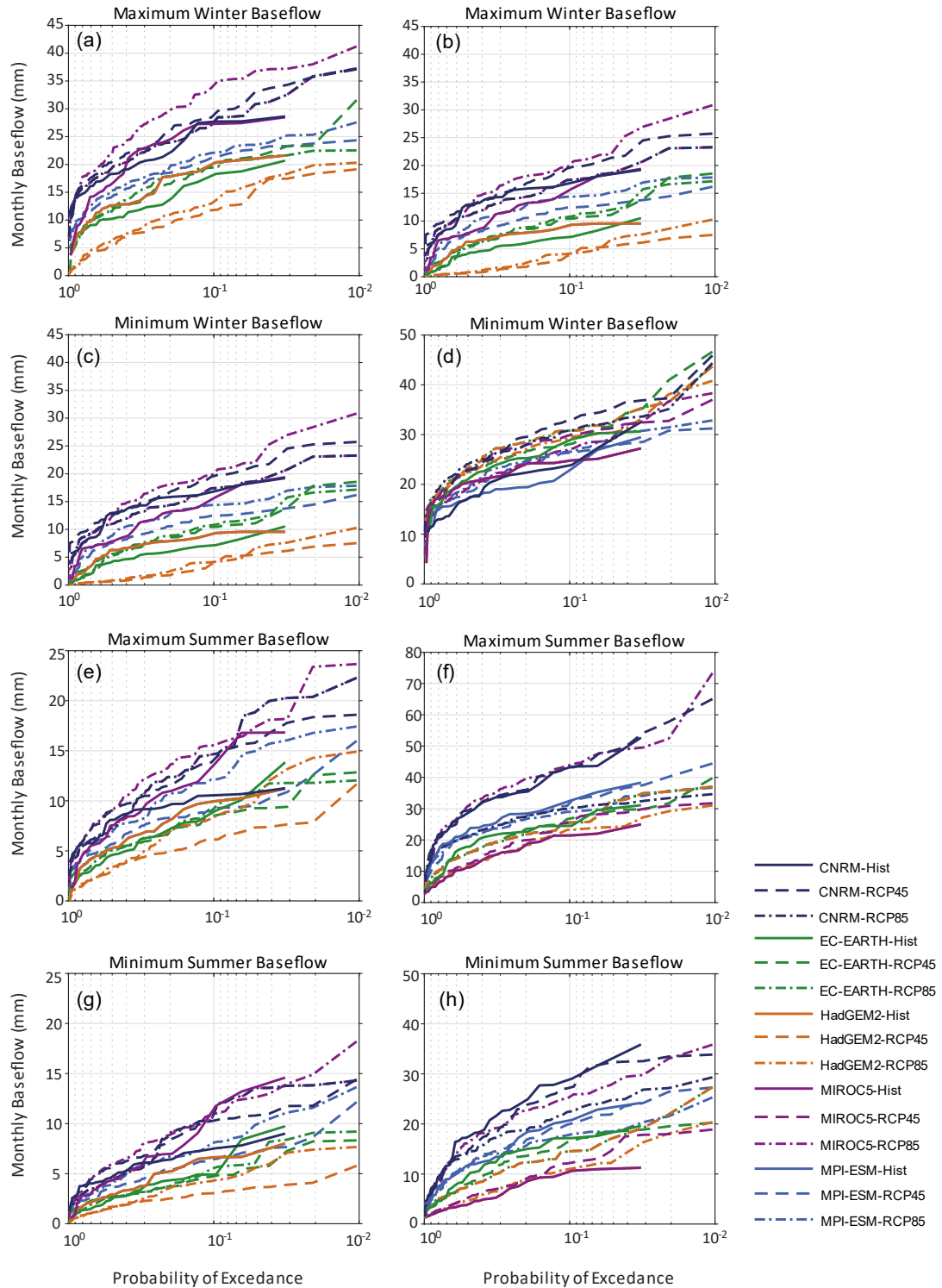


Figure 9.9 Probability of exceedance of maximum winter baseflows (a,b), minimum winter baseflows (c, d), maximum summer baseflows (e,f) and minimum summer baseflows (g, h) for the Mattock (left column) and the Dripsey (right column).

9.3.2. WT-NARX

In this section, the results obtained by forcing the selected WT-NARX models first with the climate models and second with the synthetic time series obtained from the SDSM-DC software (Wilby et al. 2002) are presented. Given the number of outputs, and the fact that the two models are structurally different, the results obtained for the two catchments are presented separately for better clarity.

9.3.2.1. *Mattock*

The best performing WT-NARX model trained for the Mattock catchment (All-WTC) uses monthly rainfall, PE and mean temperature as inputs to forecast groundwater levels at monthly time-steps up to a year. For this particular model, the three input variables are decomposed up to four levels using the procedure described in Section 8.2.2. The details are then aggregated resulting in a total of nine input features (three for each variable) as synthesized in Table 9.2.

a. Climate Projections (RCMs)

The WT-NARX model has been forced firstly with the monthly average of the input variables (i.e. Rainfall, PE, Tmean) calculated from the climate projections for each period. As in the case of the NAM, given that no bias correction has been applied, the results are interpreted as change in respect of the historical period.

Figure 9.10 shows the simulated groundwater levels (GWL) for the Mattock according to the five climate models: CNRM (Figure 9.10a), EC-EARTH (Figure 9.10b), HadGem2 (Figure 9.10c), MIROC5 (Figure 9.10d) and MPI (Figure 9.10d). All the models predict increased GWL throughout the year, for all the periods and RCPs with a few occasional exceptions.

Nevertheless, the five graphs present contrasting appearance as they simulate dissimilar groundwater table dynamics. If the GWLs for the historical period are considered (black solid lines), it becomes clear that the results obtained for the MPI and MIROC5 models are more plausible, as the predicted GWLs have a closer behaviour to the observed levels within the catchment (see Section 8.3). In contrast, the GWL simulated from the EC-Earth and HadGem2 models display a long summer recession, and reduced autumn and early winter recharge so the GWLs do not recuperate from the recession. Finally, the results obtained from the CNRM

climate model present an intermediate case, in which there is a long recession, followed by a smooth recharge period but the GWLs recover to values similar to the initial levels. Furthermore, the models that present this long recession period also display a larger spread in the simulated GWL.

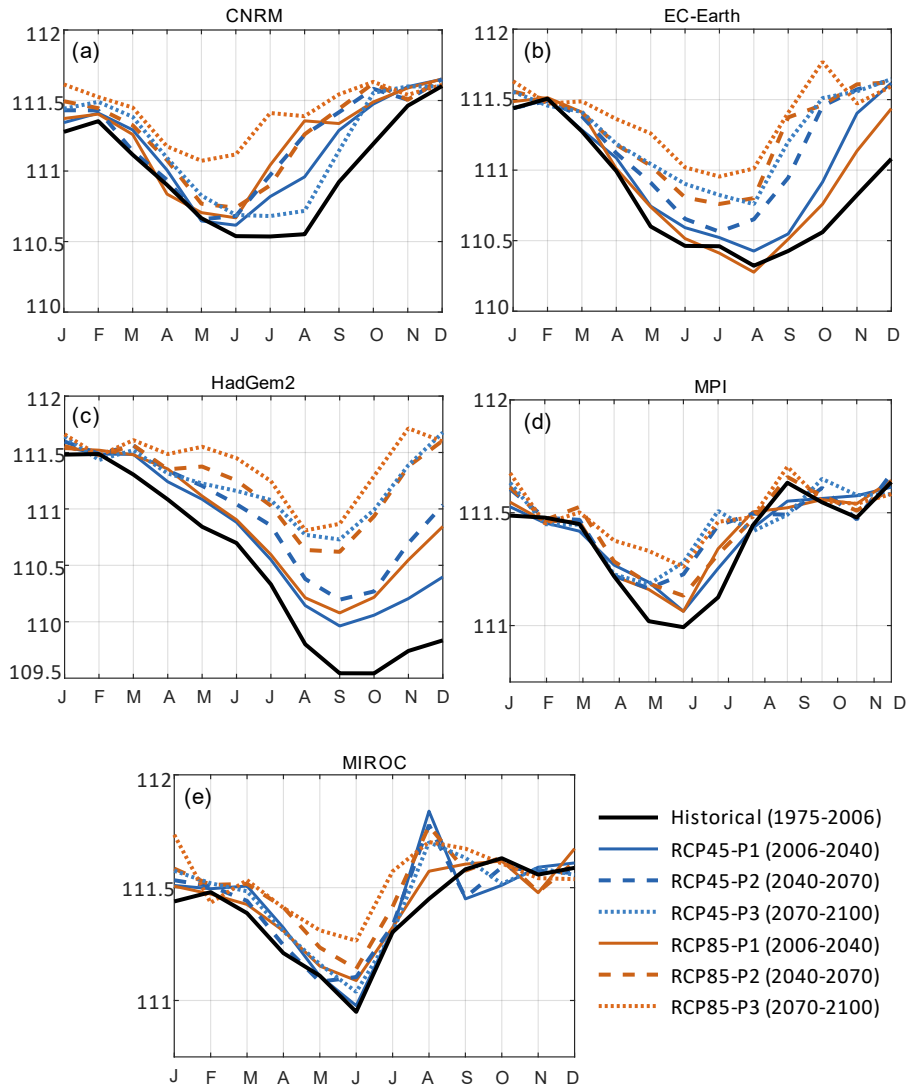


Figure 9.10: Simulated groundwater levels for the Mattock catchment from the climate models namely (a) CNRM, (b) EC-EARTH, (c) HadGem2, (d) MPI and (e) MIROC for the Historical period (solid black line) and the ‘future’ periods P1 (solid line), P2 (dashed line) and P3 (dotted line) under RCP45 (blue) and RCP85 (orange).

The differences between models originate from the discrepancies between models detected in Figure 9.2, which could also be identified in the baseflow estimations from the NAM. Consequently, in order to understand these differences, the GWL simulations need to be compared with the annual cycles used as inputs (Figure 9.11). The corresponding

figure for the Dripsey, and annual cycles calculated for the all the variables considered are presented in APPENDIX B rather than in in this chapter, for conciseness.

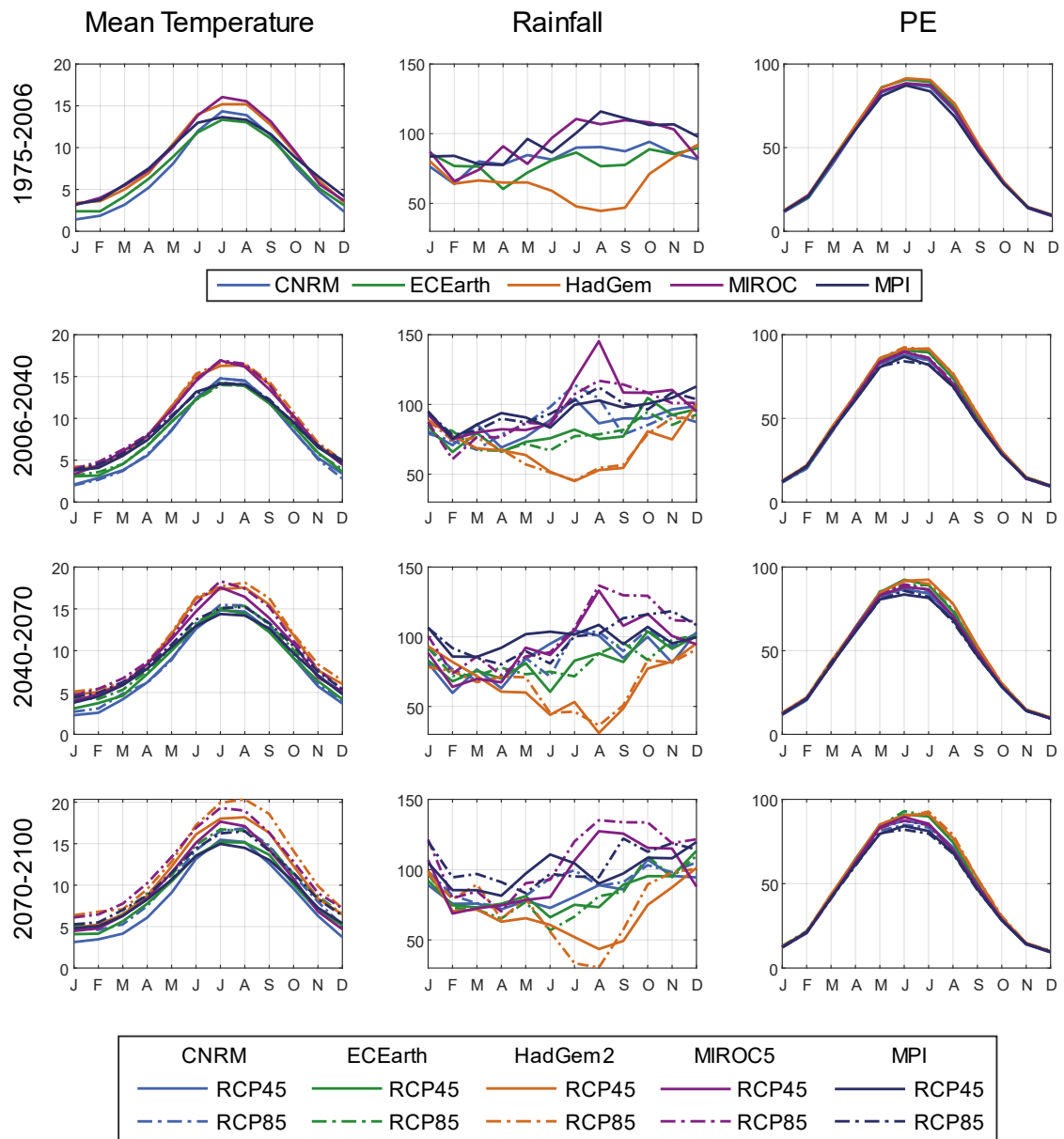


Figure 9.11: Annual cycles of the three input variables mean temperature (first column), rainfall (middle column) and potential evapotranspiration (last column) for the four periods considered: Historical (first row), P1 (second row), P2 (third row) and P3 (last row).

The annual cycles of the input variables reveal that, interestingly, the MIROC5 and HadGem2 models present the highest mean temperatures, especially for the second half of the year. However, the MIROC5 model also presents the highest rainfall amounts through the year, whereas the HadGem2 displays the lowest. Furthermore, an overall increase in the mean

temperature is observed for all the models through the periods, which, in turn, leads to a slight enhancement of the PE for autumn. The changes in the rainfall are not as obvious as there is a larger disparity between projections. Nevertheless, it can be seen that the MIROC5 model presents the larger rainfall increment, followed by the MPI whereas this increase is less acute for the other models.

Therefore, it appears that the neural networks compute the recharge or depletion of the groundwater levels based on the rainfall-mean temperature relationship as it occurs - to a certain extent - in reality and are able to reproduce plausible GWLs under contrasting climate conditions. Furthermore, models such as the HadGem2, simulate conditions where the rainfall-temperature ratio is not enough to generate groundwater recharge. These results could be pointing to critical climatic conditions from which groundwater recharge would not occur for prolonged periods of time and could result into an important depletion of the aquifer.

The range of groundwater levels forecasted for each period are displayed in boxplots in Figure 9.12. Overall, the results suggest a lower fluctuation of the GWL in the future, with an important increase of the water table for spring, summer and autumn. This would be consistent with the conceptual model of these low storativity aquifers which, are often full and are unable to accept further recharge during winters. Hence, the largest changes would correspond to summer as the GWL median increases by 1 m from the historical period to the last period (P3). Furthermore, it can be observed that the spread is decreasing for the subsequent periods providing a narrower range of GWLs, with the largest spread centred in the months of August and September.

These results are broadly consistent with the ones obtained through the application of NAM, which showed a general increase of the BFI with a maximum spread in autumn. However, the NAM showed higher increases in winter and autumn, and lower for the summer month contrary to what can be observed in the GWLs. Nevertheless, one could argue that, as described above, the groundwater levels do not rise due to the limited acceptance capacity of the aquifer, but that this excess of recharge is evacuated through the shallow bedrock towards the stream, increasing the percentage of groundwater contribution. In a similar way, the simulated increase in both, discharge and BFI during summer indicate that the baseflow itself is also enhanced, which would be consistent with higher groundwater levels.

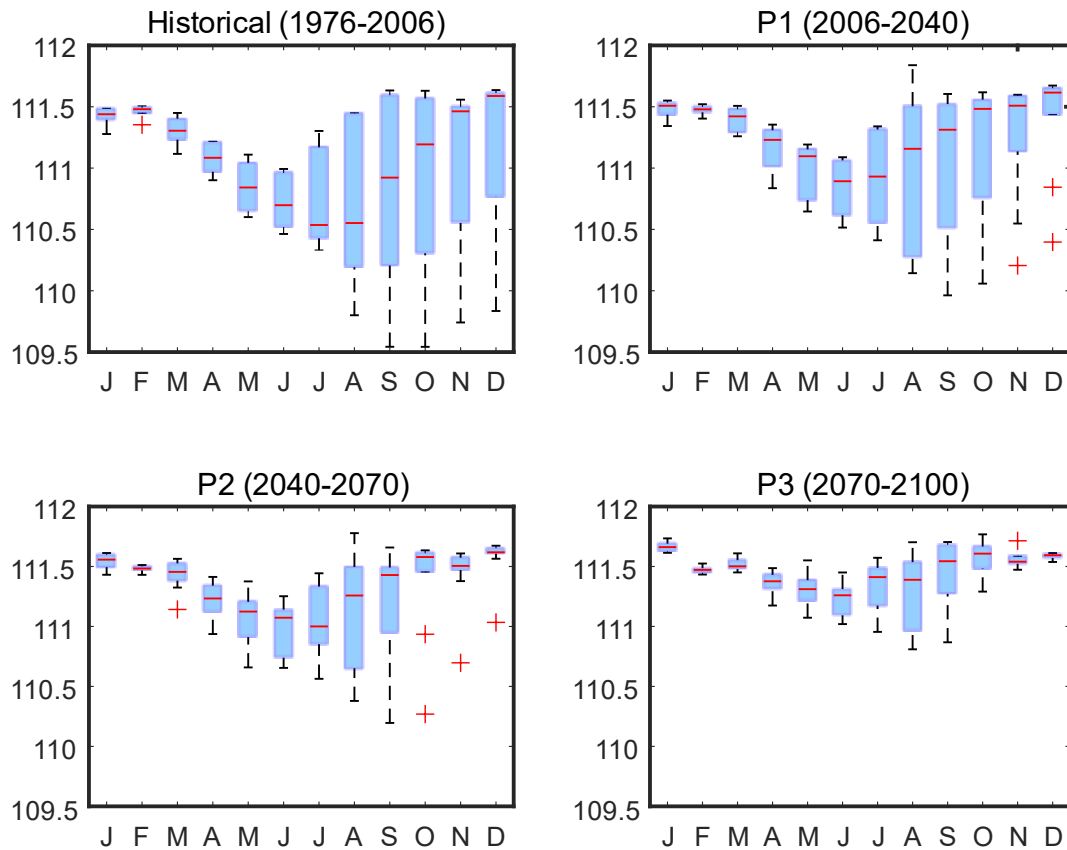


Figure 9.12: Estimated groundwater levels for the Mattock during the 4 periods considered for all the climate projections. The limits of the boxes represent the 25th and 75th percentiles, whereas the red line indicates the median (50th percentile). The extreme values (outliers) are represented by the red crosses

b. Synthetic time series (SDSM-DC)

Given the results obtained in the previous section, the WT-NARX model has also been forced with synthetic rainfall time series to investigate further the sensitivity of the aquifer system to changes in rainfall. Hence, the average rainfall observations (over the historical period) have been modified using the SDSM-DC as described in Section 9.2.1.2 and are used as reference. Nevertheless, given that these are long-term averaged observations, the outputs are expected to be smoother than when a single year is simulated like in Chapter 8.

The results obtained for both rainfall occurrence and seasonality indicate that Mattock GWLs rise in the scenarios where the precipitation is increased, as expected (Figure 9.13), and as has been observed when forcing the WT-NARX model with the climate models. However, the GWLs appear to be more sensitive to the reduction of rainfall amounts - due either to occurrence or seasonality – than to the increases. In fact, the effect of increased rainfall is

just detectable during the summer and autumn months of the rainfall occurrence (Figure 9.13a) where, after a recession period, the aquifer is able to accept recharge.

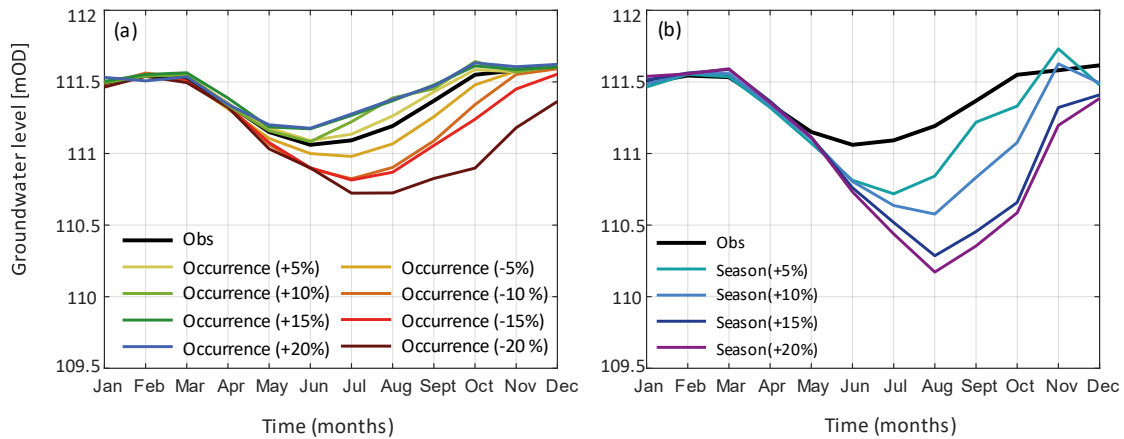


Figure 9.13: (a) Simulated groundwater levels from modified rainfall occurrence and (b) seasonality at the Mattock catchment.

This effect is just distinguishable for the two lower scenarios (occurrence +5% and +10%) as there is an overlap between the two higher occurrence scenarios (occurrence +15% and +20%). This indicates that, even though there is more rainfall, no further recharge is occurring. The same effect can be identified in the GWLs calculated with enhanced rainfall seasonality; despite the rainfall seasons have been modified to increase the rainfall for the months of December, January and February there is no distinguishable effect for the two later.

In contrast, the scenarios in which a rainfall reduction is simulated through occurrence or seasonality, have a clear impact on the magnitude of the recession, which propagates until the end of the simulated year. However, none of the cases tested by this approach reaches the depletion levels observed for the EC-Earth and HadGem2 models, suggesting that further rainfall reduction (or seasonal amplification) is needed for the aquifer to reach such critical state.

On the other hand, it must be emphasised that the enhanced rainfall of seasonality scenarios has a limited effect on the volume of groundwater stored, given the insensitivity observed, which is most likely to be mimicking the limited storage capacity of this aquifer. Consequently, it is probable that dryer springs and summers could lead to critical depletion states such as the simulated by the aforementioned climate models.

9.3.2.2. *Dripsey*

As it has been done previously for the Mattock, the best performing WT-NARX model obtained from Chapter 8 (PE-T-WTC) is used here to simulate future groundwater levels under contrasting climatic conditions. However, in this case, out of the three input variables just the rainfall is decomposed up to four levels, whereas PE and mean temperature are left undecomposed resulting in a total of six inputs as described in Table 9.2

a. Climate Projections (RCMs)

Figure 9.14 shows the simulated groundwater levels (GWLs) for the Dripsey according to the five climate models: CNRM (Figure 9.14a), EC-EARTH (Figure 9.14b), HadGem2 (Figure 9.14c), MPI (Figure 9.14d) and MIROC (Figure 9.14e). Overall, the simulated GWLs present a similar range of changes to those obtained for the Mattock; however, the groundwater table dynamics represented appear to be unrealistic. This is especially obvious for the historical periods of the CNRM (Figure 9.14a), and MIROC (Figure 9.14e) as they display almost periodic peaks of similar amplitude and duration instead of the expected smooth progressive recession typical of spring and summer months. Furthermore, these results show little sensitivity to the changes in inputs as the graphs display small variations in the simulated groundwater levels under the different periods and RCPs. Overall, the only conclusion that can be drawn from these results is the agreement by almost all the models for a depletion of the GWLs during summer and autumn, the magnitude of which depends on each model.

Given the implausibility of the simulated groundwater levels no further analysis of this set of results is performed as, at this point, it is not possible to discern if it is caused by structural limitations of the model, the inputs, or the decomposition process.

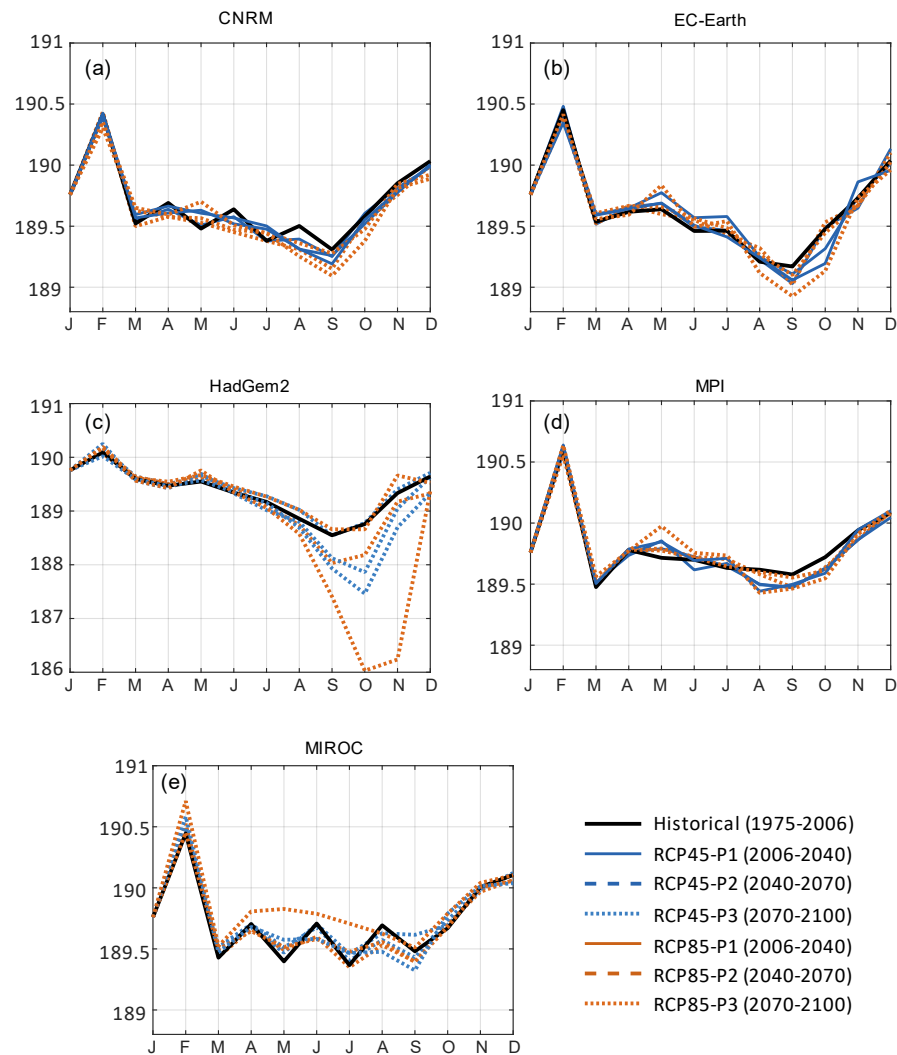


Figure 9.14: Simulated groundwater levels for the Dripsey catchment from the climate models namely (a) CNRM, (b) EC-EARTH, (c) HadGem2, (d) MPI and (e) MIROC for the Historical period (solid black line) and the ‘future’ periods P1 (solid line), P2 (dashed line) and P3 (dotted line) under RCP45 (blue) and RCP85 (orange).

b. Synthetic time series (SDSM-DC)

The WT-NARX model trained for the Dripsey has also been forced with the synthetic time series generated by the SDSM-DC in order to simulate changes in rainfall occurrence and seasonality.

The results obtained by this approach, unlike those from the climate projections, simulate plausible groundwater levels (Figure 9.15).

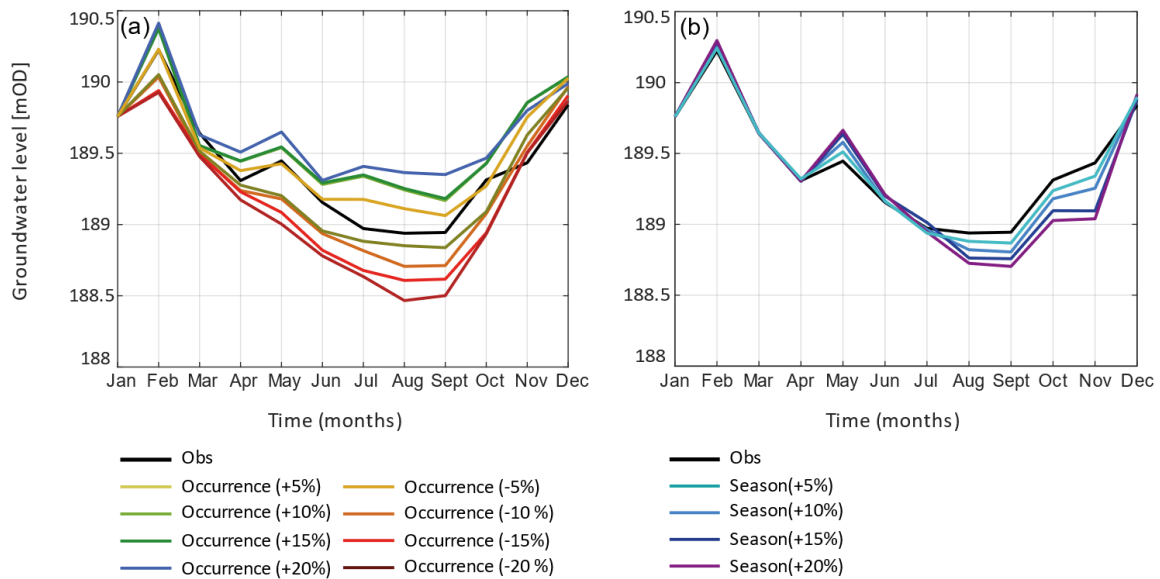


Figure 9.15: (a) Simulated groundwater levels from modified rainfall occurrence and (b) seasonality for the Dripsey catchment.

The results indicate that increased (reduced) rainfall leads to a rise (depletion) of the groundwater levels, as would be expected. Similar to what was observed for the Mattock, the GWLs appear to be more sensitive to reductions in rainfall than to increases, especially for the winter months where the aquifer is more likely to be full. Therefore, even though the changes in rainfall occurrence affect the groundwater levels throughout the year, they have a larger impact from May to October when the recession period has typically started. Hence, the aquifer is able to accept further recharge if rainfall is increased but the recession is enhanced if the wet-day occurrence is reduced (Figure 9.15a). On the other hand, the alteration of the rainfall seasonality suggests an increase in groundwater recharge in May and a reduction from July to November, even though these changes appear to have a smaller impact on the GWL than those induced by the changes in rainfall occurrence.

9.3.2.3. WT-NARX models comparison

The results presented in this section indicate that the two WT-NARX models lead to dissimilar simulated GWLs when forced with the climate models; even though the results obtained for the Mattock are plausible, the GWLs simulated for the Dripsey appear to be unrealistic, despite there being no major differences in the input climate simulations. Therefore, the

cause of these unrealistic results must be either in the structure of the model itself or in the inputs decomposition. However, the differences between models may stem from the differences in hydrogeological characteristics of the catchments (see Section 7.2.1.2 and 8.3). To further investigate the reason for this uneven performance of the WT-NARX models, an additional analysis has been performed to identify the relative importance of each input feature for each model.

When a NARX model is created, random initial weights are given to each input feature to initialize the neural networks (see Section 8.2.4). These initial weights are often referred to as input-hidden layer connection weights as they condition the information transmitted from the inputs to the hidden layers (or neurons). Then, during the training process, further weights are assigned for each hidden layer in relation to the outputs. These weights are referred to in the literature as hidden layer-output connection weights.

There are a number of techniques to estimate the relative importance of the input features in relation to the output achieved. In this case, Garson's algorithm (Garson 1991) has been implemented due to its relative simplicity and because it is used in ecological sciences (e.g. Olden and Jackson 2002; Gevrey et al. 2003; Olden et al. 2004), as no similar study has been found for hydrogeological studies. The original method proposed by Garson (1991) and repeated by Goh (1995) consists of partitioning the connection weights presented above in order to establish the relative importance of various inputs. Here, the simplification of the algorithm proposed in Gevrey et al. (2003) has been implemented as it leads to the same results.

The outputs of these calculations show the relative importance of each input expressed as a percentage, as presented in the bar graphs in Figure 9.16. Because of the in-built autoregressive structure of the NARX models, the regressed GWL values used during the training to inform the neural network are also considered as inputs.

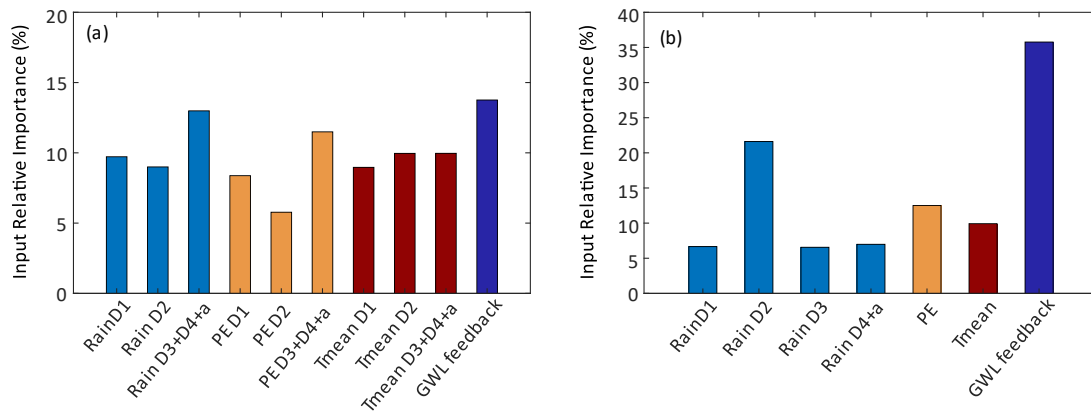


Figure 9.16: Relative importance of the inputs used in the NARX model for (a) the Mattock and (b) the Dripsey. D stands for detail and a for approximation referring to the outputs of the MODWT-MRA decomposition. GWL feedback corresponds to the auto regressed groundwater levels information within the NARX.

In both cases, the most important input appears to be the regressed groundwater level information. In the case of the Mattock, the relative importance of GWLs is less than 15%, and the relative importance of all the inputs is distributed evenly. For instance, the third rainfall input and the third PE input present similar values. In contrast, the distribution of the relative input importance is highly uneven for the Dripsey: the auto regressed GWLs represent up to 35 %, followed by 23 % for the second rainfall input (Rain D2).

On the one hand, the dependence on the GWLs values could be leading to a lower stability of the NARX when forecasting future GWLs as this information is not available. On the other hand, the second input of the rainfall (Rain D2) corresponds to the second detail obtained from the MODWT-MRA decomposition. This detail has associated periods from 3.5 to 9 months, which are likely to be highly variable within the climate projections. Therefore, the unrealistic geometries found in the results for the Dripsey are likely to be representing the variability of this detail. Finally, the third inputs of the rainfall and PE in the Mattock mentioned above (second and third most important inputs for that model), correspond to the longer-term variations (7.3 to 35 months), which typically present smoother changes. Hence, these results could be suggesting that neural networks where the input features corresponding to long-term variations have a higher importance, could be more stable and, consequently, more suitable for climate change impact assessments.

9.4. Conclusions and Discussion

In this chapter, the possible impacts of climate change were evaluated within the two main study areas considered in this thesis, the Mattock and Dripsey catchments. To achieve this, two distinct methodologies have been applied: (1) A classical rainfall-runoff model has been forced with climate projections, and (2) the WT-NARX models developed during Chapter 8 have been used to forecast groundwater levels from climate projections, and synthetic rainfall time series have been modified to represent the expected increase in rainfall occurrence and enhanced seasonality. Since the application of neural networks to climate change assessment is a novel approach and there is no literature on this topic, the aim of this chapter was not just to evaluate the impacts of climate change, but also to assess the suitability of this novel methodology more generally for groundwater resources impact assessment studies.

The forcing of the NAM with climate projections for the historical period (1976-2006) and the three “future” periods (2006-2040, 2040-2070 2070-2100), has provided a range of likely baseflow change. Overall, when every set of generated baseflow scenarios are considered, the results suggest a monthly change of $\pm 50\%$ for the Mattock and $\pm 100\%$ for the Dripsey. However, if these results are represented in boxplots, a general positive change signal is observed, suggesting an increase in baseflow index would represent up to 25 % of the river discharge. Although these values are higher than the baseflow estimation obtained with the NAM (17 %) they are similar to the recharge estimations obtained through the baseflow separation (up to 23%) and are consequently considered as plausible.

Even though the same positive signal is identified in the Dripsey, there is a clear seasonal fingerprint with a larger enhancement in the BFI for March up to 70%. Based on the knowledge of the catchment and the previous recharge calculations, it is considered unlikely for the baseflow index to be higher than 40% in the Dripsey catchment, that is an increase by 35%. Furthermore, the probability analysis has indicated an increase in both maximum and minimum winter baseflows. However, the signal is not as clear for the summer probability plots as it changes through the series. In summary, despite the large inherent uncertainty of this approach it is useful for providing an order of magnitude of the possible changes, and a statistical characterisation of likely future conditions.

In contrast, the simulated GWLs obtained by forcing the WT-NARX models with climate projections provide a narrower range of changes, with a clear positive signal suggesting a rise in the groundwater levels, which is consistent with the findings of the NAM. Despite the uneven performance of the WT-NARX models, the results show that these models can simulate the water table dynamics under a range of climate conditions. Consequently, the WT-NARX models constitute a suitable tool for groundwater impact assessment studies and are particularly useful for stress-testing purposes. Nevertheless, as this is - to the knowledge of the author - the first application of WT-NARX models, in this way, they need to be further developed to have produce more robust models and consistent performances.

Additionally, the lowest groundwater levels simulated for the Mattock when forced with climate projections, together with the results obtained with the SDSM-DC, suggest that the neural networks models have indeed the capacity for learning and establishing correctly the relationship between input features such as rainfall and temperature. However, the conditions represented by the climate models are dissimilar to those registered in the observations and, consequently, the model transferability is challenged. Even though the results may seem to simulate unrealistically low groundwater levels and long recessions, these outputs could be pointing at critical climate conditions from which the aquifer would enter in recession. Hence, further stress-testing is required to identify possible critical rainfall and temperature values for the aquifer. Also, the existence of these threshold values should be further investigated by stress-testing the system with modified time-series and will be considered for future work.

The poor performance of the WT-NARX model applied to the Dripsey can be explained by: (1) the contrasting climate conditions represented by the climate models and (2) the relative importance of the input features, which, in turn, are an indirect consequence of the hydrogeological properties of the catchment. As the models were selected based solely on their performance, this could not have been known *a priori*. For this reason, and based on the results obtained, screening of the relative input importance is strongly recommended for any future applications. Moreover, this should be included as a selection criterion in order to find the most suitable model, since the results indicate that a more even distribution of the relative importance of the inputs could lead to more stable models. Also further research on the effect of the relative input importance is required for a more accurate application of the WT-NARX models to climate change impact assessments. For instance, the Garson's algorithm has been applied in this chapter as it is widely used for this purpose in ecological

studies (e.g. Olden and Jackson 2002; Gevrey et al. 2003; Olden et al. 2004; Ibrahim 2013) and it is relatively easy to implement. However, some authors (e.g. Olden et al. 2004) have pointed out the limitations of this method and recommend the application of other more complex approaches such as sensitivity tests. Here, the further implementation of such tests was prevented by the 'opaque' architecture of the NARX models in MATLAB and has not been possible within the framework of this thesis.

Given the results presented above, the application of the conventional rainfall-runoff modelling forced with climate projections could appear more stable and suitable for groundwater resources evaluation under a changing climate. However, this 'top-down' approach is not exempt of limitations in model transferability. When models such as NAM are applied for this purpose, there is an important assumption of parametric stationarity; in other words, the selected set of parameters are assumed to generate realistic simulations under contrasting hydrometeorological conditions to those used for model development (Broderick et al. 2016). This is a well-known issue in hydrological studies (e.g. Hartmann and Bárdossy 2005; Wilby 2005; Beven 2006; Merz et al. 2011; Thirel et al. 2015a, b), and a few hydrogeological studies have addressed the intrinsic structural uncertainty of the models commonly applied (e.g. Holman 2006; Döll and Fiedler 2008; Cuthbert and Tindimugaya 2010; Crosbie et al. 2011; Bastola et al. 2012; Hartmann et al. 2012; Moeck et al. 2016), but model transferability has not been directly quantified in any of them. Broderick et al. (2016) tested a number of hydrological models - including the NAM - for 37 different catchments within Ireland and make a list of recommendations such as adopting a multi-model ensemble with an objective averaging technique to combine members and evaluate the model transferability using a range of climate analogues, catchment types and performance criteria.

In summary, the model transferability for the WT-NARX models is clearly controlled by the length of the training dataset and the diversity of climatic regimes that has been used during the training process. However, despite being less obvious, the conceptual rainfall-runoff models present the same problems through the assumption of parametric stationarity. Additionally, the higher model stability can lead to unrealistic outcomes being unnoticed. Hence, model transferability is an important issue that should be considered in impact assessment studies in hydrogeological sciences regardless of the type of model applied. As a matter of fact, the clear display of the transferability limits within the WT-NARX models could be an advantage if the detected limits on the WT-NARX transferability are extrapolated to other models - such as NAM - that do not display these limits as clearly. This would constitute

yet another novel application of the WT-NARX models and could improve the robustness of future impact assessments.

The results of this chapter demonstrate both the potential, as well as the limitations, of the methodology developed during this thesis. As a novel approach, it requires further research, especially on the input feature selection and model transferability when forced with contrasting signals. Therefore, future work focused on establishing an improved framework and methodology is necessary. Further detailed discussion and recommendations are presented in Chapter 10.

10. Conclusions and Discussion

10.1. Introduction

There is little doubt remaining about the reality of ongoing climate change: The anticipated enhancement of climate extremes (Gleeson et al. 2013) is expected to cause an intensification of the hydrological cycle with longer droughts and more frequent flooding events. In fact, anthropogenic activities have altered the Earth's climate to the point that the stationarity of the hydrological processes can no longer be assumed (Milly et al. 2008). Nevertheless, it is also well-known that the magnitude of climate change is strongly dependant on local and regional characteristics (Bates et al. 2008).

Given the large storage capacity of aquifer systems, groundwater resources present a higher resilience than surface water resources and can buffer climate extremes such as droughts. In the Irish context, the natural resilience of groundwater resources, combined with the humid climate and the relatively low population density, has preserved the groundwater resources that have not been generally regarded as being under stress despite some historical drought events (Wilby et al. 2016; Murphy et al. 2020). However, in recent years longer dry spells such as the exceptionally dry summer in 2018 (Falzoi et al. 2019) have put the resilience of Irish groundwater resources at stake. Moreover, a large percentage of Irish bedrock aquifers have a limited storage capacity which also limits their resilience. In this context, this PhD dissertation has aimed to evaluate how some of the characteristic Irish hydrogeological features that constrain groundwater recharge, and to assess the impact of a changing climate on low storativity fractured bedrock aquifers.

The sensitivity analysis carried out (Chapter 4) showed that the storage capacity is the main limiting factor in the areas underlain Poorly Productive aquifers. This limited storage capacity was also observed when calculating groundwater recharge through the water table fluctuation method (Chapter 6): in wet periods (or seasons) when there are frequent recharge events the observed groundwater levels often present a "*roof effect*" as they reach a maximum level that is not exceeded. In these cases, the corresponding calculated groundwater recharge is low in proportion to the accumulated monthly precipitation, indicating that the aquifer is full, and unable to accept further recharge (Figure 6.8). In

contrast, the largest recharge events occur after prolonged recession periods (e.g. autumn), when the aquifer has the capacity of accepting large volumes of water. These results would suggest that, in terms of climate variability, Irish groundwater resources are more vulnerable to alterations in recharge patterns during the dryer months as the aquifer's depletion could be either enhanced (i.e. longer and dryer summers) or smoothed (i.e. increased storminess) by the changes in seasonal precipitation patterns. This is consistent with the results presented later in Chapter 9, by the forcing of the WT-NARX models with the synthetic rainfall series (SDSM-DC): as Enhanced rainfall occurrence and seasonality caused little differences in the winter groundwater levels, but had a larger impact from the end of spring to the beginning of autumn, by modifying the length and intensity of the summer recession.

Furthermore, the sensitivity analysis also showed that the recharge coefficients and so the infiltration processes through the unsaturated zone, govern groundwater recharge when the underlying aquifer does not have a restricted storage capacity. To further investigate the effect of the overburden, the infiltration capacity of two additional study sites was approximated through the implementation of Hydrus 1D model at both sites. The results show that, in order to generate runoff by excess of saturation, rainfall intensities between 6.5 and 12 mm/h are required, depending on the depth of the water table and the saturated hydraulic conductivity of the subsoils. It should be noted, however, that both sites have associated recharge coefficients of 60 % and hence further research is required to assess the infiltration capacity in lower permeability soils and subsoils.

Once it had been established how the bedrock properties control groundwater recharge, the relationship between the main hydrometeorological variables and groundwater levels was analysed in Chapter 7 through the application of Continuous Wavelet Transforms (CWTs) and Wavelet Coherence (WTC). Specifically, the cyclicity of the different signals was analysed through the CWTs and then the rainfall-recharge relationship was analysed through the WTC of the two signals at daily resolution. The results revealed that the linearity of such relationships is strongly dependant on the structural characteristics of each catchment and, more particularly, on the presence of a well-developed Transition Zone at the top of the fractured and weathered bedrock.

Furthermore, it is crucial to understand the influence of the natural climate variability on groundwater resources in order to better assess the possible changes caused by climate change. It is well known that large-scale circulation patterns can explain a large proportion

of the low-frequency climate variability and, consequently, multiannual groundwater dynamics. For this reason, the connection between these climate indices and the groundwater levels was also investigated in Chapter 7.

Overall, the findings up until Chapter 7 highlight the critical role that the physical and structural properties play on the infiltration and recharge processes. Moreover, these results also indicate that some of these properties could influence the magnitude of the possible impacts of climate change. Therefore, to be able to account for the aquifer's physical properties when forecasting groundwater levels, Chapter 8 focused on developing and implementing a WT-NARX model for the two main study catchments (i.e. Mattock and Dripsey).

The methodology used involved the decomposition of the input signals through Maximum Overlap Discrete Wavelet Transforms (MODWT) that were then aggregated according to different criteria and fed into the NARX model. The trained WT-NARX models achieved excellent performances for both study catchments despite being slightly higher for the Mattock.

Groundwater climate change impact assessments have typically been carried out by implementing conceptual rainfall-runoff models (such as NAM) from which either baseflow or groundwater recharge can be estimated. In this thesis, the NAM rainfall-runoff model implemented in Chapter 6 was used, in conjunction with climate projections, to generate baseflow simulations until 2100. Additionally, the WT-NARX models were also forced with the averaged climate conditions represented by the climate projections but also by synthetic rainfall series to simulate enhanced rainfall occurrence and seasonality.

The results obtained by forcing the NAM with climate projections provided a statistical characterisation of the possible future scenarios, and a long-term assessment of the impacts according to the input climate conditions. In contrast, the WT-NARX have proven useful for short-term forecasts and stress-testing of the system, i.e. for the identification of critical (or threshold) values.

The conclusions from each topic addressed during this dissertation are presented below, highlighting the novel aspects and the contribution to knowledge. Future work and recommendations for further research outlined at the end of this chapter.

10.2. Sensitivity analysis

The sensitivity analysis presented in Chapter 4 consisted of testing the influence of the main hydrogeological and hydrometeorological variables on groundwater recharge at different scales. The results show that the local hydrogeological settings have a larger control on groundwater recharge than the tested climate variability, with the aquifer's storage capacity being the main limiting factor. Consequently, this would lead to an unequal impact across the country, owing to the heterogeneous nature of the hydrogeology as evidenced in the results for the Nuenna catchment. These results are consistent with the existing literature, as it is known that, in humid regions like Ireland, where the aquifers are often full, the recharge rates are limited by the aquifer's storage capacity, which is in turn affected by the subsurface geology (Scanlon et al. 2002). Furthermore, it is also acknowledged that local physical characteristics can modify the magnitude of the impacts of climate change (Bates et al. 2008). Despite not being novel, these results have provided a solid baseline for the research project and can be used at the Irish level to identify the most vulnerable areas to climate change.

10.3. The unsaturated zone and infiltration capacity

The evaluation of the Potential Evapotranspiration methods presented in Chapter 5, and the evaluation of the impact of changes of rainfall on the soil moisture budget parameters is a continuation of the sensitivity analysis, as its results pointed out that the processes involved in the unsaturated zone are the second most important limiting factor within the Irish context. The results obtained showed that the modified Penman-Monteith equation is sensitive to the available data, as the substitution of net radiation measurements by estimates lead to a slight overestimation of the PE in some catchments. Nevertheless, the simpler Hargreaves-Samani equation appears to provide closest values so it constitutes a good alternative when the meteorological data required for the Penman-Monteith equation is not available.

In the second part of this chapter, the infiltration capacity of the soils is assessed for two additional study sites as the data required for this type of modelling was not available for the main study catchments. The modelling process highlighted the importance of the spatial and temporal discretization in highly nonlinear systems, as the results obtained at daily and

hourly resolution differed substantially. However, it was possible to establish a threshold of rainfall intensities from which runoff would occur for each study site. Both study sites are on moderately permeable soils with associated recharge coefficients of 60%, overlying carbonate aquifers, according to the national recharge map (Hunter Williams et al. 2013). These results suggest that infiltration processes are dominant in areas with a corresponding recharge coefficient of 60% or higher. However, to be able to upscale and generalise these results, the same approach should be applied in a range of areas with similar and contrasting characteristics building on the results obtained by Fitzsimons and Misstear (2006). Additionally, it should be noted that this assessment was conducted for relatively high permeable soils and that, in the future it should be applied to soils with poor permeability.

Furthermore, it must be kept in mind that a large proportion of Irish aquifers have a restricted storage capacity, which is translated into 'rejected recharge' when the aquifer is full and cannot accept further recharge. Hence, these results call for an integrated modelling of the unsaturated zone and the recharge processes in order to bridge the knowledge gap and better understand the interactions between the saturated and unsaturated zone.

10.4. Recharge Characterisation

The recharge characterisation presented in Chapter 6 combined up to 5 recharge estimation methods. This modelling exercise lead to constraining of groundwater recharge estimates to relatively narrow ranges, considering inherent uncertainty of the recharge calculations. Of all the methods applied, the Water Table Fluctuation was the most informative, as it provided valuable information about the catchment heterogeneities and conceptual models, while evidencing the limited storage capacity of the aquifers. Moreover, it also highlighted the seasonality of recharge events as outlined at the beginning of this chapter. Hence, it is recommended to use this method when possible because, being based on a rainfall-groundwater levels relationship, it provides provide more information than other methods.

The implications of the findings of this chapter are most significant at the Irish level: on the one hand, because the Dripsey catchment had not been studied in detail from the hydrogeological point of view and, on the other hand, because the results put into discussion the established recharge caps values, but also the concept itself as it has been shown that these caps should be state – and time - dependant. Moreover, this chapter also provides a

simple methodology to compute an effective S_y value at catchment scale, one that can be used for groundwater resources assessment studies. Although of particular interest in highly heterogeneous aquifers, this approach could be used in any type of aquifer as long as there is groundwater level information.

10.5. Climate variability and groundwater level dynamics

Chapter 7 addresses the need to better understand the effect of climate variabilities on the groundwater levels at high frequencies (i.e. daily rainfall-GWL WTC) but also with the main drivers of low-frequency climate variabilities (i.e. Teleconnection Patterns). This is especially important in the framework of a climate change impact assessment study, as several authors have shown that the GCMs cannot fully represent these large-scale patterns (Stephenson et al. 2006; Furtado et al. 2011; Lapp et al. 2012). However, these phenomena present long periodicities that could not be captured using the limited record of groundwater levels for the Mattock and the Dripsey. Therefore, an additional long-term monitoring point, the Knocktopher borehole in Co Kilkenny, was added to provide context and examine the effect of these patterns at longer timescales, while the Mattock and the Dripsey were to look into the effect at shorter time scales (seasonal to multiannual).

As presented at the beginning of this chapter, the results of applying the wavelet coherence at daily resolution revealed the geological differences in the catchments, while highlighting the role of the transition zone as a preferential pathway. However, as most of the infiltrated water is transmitted laterally as interflow, the presence of a well-developed transition zone shadows the recharge signal directly underneath, in the shallow bedrock. The relationship between rainfall and groundwater levels is, therefore, more linear and direct in the case of the Mattock catchment as it does not have a well-developed transition zone.

The analysis of the interaction between climate indices and groundwater levels revealed that all the indices have a certain effect on the variability of the groundwater levels. The sensitivity of the catchments to each index is, however, controlled by the local strength of the signal between the index and the rainfall. In the case of a strong correlation, the indices that have a clear seasonal fingerprint (i.e. NAO, AMO) are found to affect groundwater seasonality and not just long periodicities. Finally, the Greenland Blocking Index has been relatively less studied in comparison to the other indices and consequently, there are still some questions

about its mechanisms. The results show that the GBI and NAO mirror almost perfectly each other, which is consistent with the findings of Woollings et al. (2008) and Hanna et al. (2018) as the occurrence of one implies the absence of the other or, in other words, the two indices mirror each other.

Fractured bedrock aquifers are not just common in Ireland but worldwide, one of their characteristics being the shallow layer of weathered and fractured bedrock that in Irish terminology is known as Transition Zone (Comte et al. 2012). The findings regarding its role on the infiltration and recharge processes are thus potentially a valuable contribution to knowledge more widely than Ireland.

Furthermore, this chapter provides an assessment of the relationship between the large-scale climate patterns and the groundwater levels, which had been never performed in Ireland before. The results are, in general, consistent with the existing literature. However, this chapter adds a significant contribution to knowledge, as none of the previous studies had considered the impacts of these forms of climate variability in the short-term. The results demonstrated that some of these indices can also have an important impact at seasonal scale, as mentioned above.

This finding can have significant implications in terms of water resources management and flood prevention in humid regions such Ireland, and especially in low-storativity fractured aquifers. For instance, a strong AMO signal over summer leads to higher than average recharge during this season, and the aquifer does not enter into a significant recession. Then, in the wet season, the aquifer would get full faster, and unable to accept further recharge, making certain areas more vulnerable to surface water flooding and groundwater flooding. This is even more evident with the winter NAO, as significant flooding and groundwater flooding events have been linked to strong positive phases during winter.

10.6. WT-NARX models

The development of the WT-NARX models presents a solution to representing the aquifer properties under future climate conditions. As the machine learning techniques, and particularly the artificial neural networks (ANN), are becoming more common in hydro(geo)logical sciences, several studies have already implemented similar models to

forecast groundwater levels in contrasting geological settings. Hence, several authors have already applied NARX models, while others have coupled wavelet transforms (and MODWT) to ANN. However, there was no evidence found in the literature of prior studies proposing the coupling of MODWT with NARX. The novel aspect of the proposed approach is to group the decomposed details to (i) reduce the number of inputs and (ii) give physical- meaning to the input features. Moreover, even though the Bilog graphs have been used in similar applications, the Wavelet coherence had never been applied in such way previously (to this author's knowledge).

It was found that the choice of the detail aggregation criteria - and number of inputs - have a strong control on the performance, since a poor choice of input features can often lead to overfitting. This became evident in the physically based aggregation criteria (i.e. WTC and Bilog Graphs) as the number of inputs depends on the complexity of the system. Hence, when the complexity of the catchment requires a higher resolution of the input features (i.e. higher decomposition level), it is translated into a larger number of input features, and overfitting is more likely to occur, as was observed for the Dripsey. In this particular case, the presence of the transition zone is translated into a more complex relationship between the inputs and the target (i.e. rainfall-groundwater) which, in turn, leads into a lower performance of the model.

The results indicate, that these NARX models can be used to forecast groundwater levels with relatively scarce data, as other authors have previously pointed out (e.g. Wunsch et al. 2018), and that the coupling with the MODWT generally improves their performance as long as overfitting does not occur. As this field is still under development, there are a number of implications, and future research lines are opening. For instance, further research on the optimal detail aggregation criteria should be pursued in order to establish these beforehand rather than relying on a trial and error approach. The most urgent problem to tackle is the overfitting, as it is a common issue when applying machine learning techniques in environmental sciences. In summary, in this chapter a novel input feature selection criterion in ANN models has been applied and hence is contributing to a field of research under development such as machine learning techniques.

10.7. Climate Change Impact assessment

Once the control exerted by both the hydrogeological features and climate variability on groundwater recharge was better understood, it was possible to conduct a climate change impact assessment. For this purpose, two different approaches were used: (i) a classical approach forcing the NAM model with climate projections (RCMs), and (ii) using the best performing WT-NARX model for each catchment to estimate the groundwater levels under the climate conditions simulated by the RCMs, but also using synthetic rainfall series to stress-test the system.

The two methodologies followed are evidently contrasting in principle but also provide different answers to the same question. The forcing of the NAM with climate projections provides a number of long-term scenarios, with significant differences between them that stem from the disparity between climate models. However, this kind of approach can be useful to establish the signal of the possible changes (i.e. increase or decrease of a specific variable), as well as analyse trends and changes in frequency of extreme events.

In contrast, as long as the WT-NARX models are under development, and their prediction capacity is limited to one year, their applications for this objective are also restricted. Nevertheless, the results obtained have shown that these models can simulate groundwater levels under contrasting climate conditions. Furthermore, the fact that this makes it possible to implicitly account for the specific local characteristics makes them especially suitable. Therefore, even though these models cannot currently be used for long-term forecasts and trends analysis, they constitute a good tool to stress-test the systems.

Both methods agree on forecasting an increase in groundwater recharge when forced with climate projections. The NAM simulations forecast an overall increase of the baseflow as a direct consequence of an enhancement of river discharge. The largest increments are detected for winter and autumn. In contrast, the WT-NARX models show little increase for these seasons, when the aquifers are full, and an important rise of the groundwater levels during the dryer months. Similar results are obtained when the WT-NARX are forced with synthetic time series simulating an increase in rainfall occurrence. However, it must be kept in mind that the two methodologies measure different variables. Despite appearing contradictory, these results are not mutually exclusive. For instance, a larger groundwater baseflow contribution during winter could occur despite not being reflected in the

groundwater levels. If the aquifers are full, the excess of recharge (or rejected recharge) would be transmitted through the shallow bedrock to the streams. However, the main conclusion that can be drawn is that groundwater levels are more vulnerable to changes occurring during dry periods when the groundwater levels recession can be either enhanced or reduced depending on the climate variability. Nevertheless, the simulated increase on river discharge during wintertime, together with the inability of the aquifers to accept recharge, could have serious implications in terms of flooding.

The results obtained with the WT-NARX model for the Dripsey catchment demonstrated the limits of the transferability of these models. These issues could be largely solved by considering the relative importance of the input features in the WT-NARX model selection rather than basing it solely on the performance. However, it must be kept in mind, that the differences between the WT-NARX models obtained from the Mattock and the Dripsey, are a consequence of the physical differences between the two study catchments. As noted above, the presence of the transition zone at the Dripsey leads to a more complex relationship between the hydrometeorological variables and the groundwater levels, which is translated into a poorer performance, as the ANN needs to recognize and establish more complex patterns. Hence, it is also logical that the back-propagated groundwater levels are the most important input for the Dripsey.

This chapter provides an assessment of the possible climate change induced modifications on groundwater systems through two contrasting approaches. Furthermore, it also explores the applicability of machine learning techniques for climate change impact studies, which is a novel contribution to knowledge at international level. Despite the rising interest in these techniques, none of the previous studies had investigated the relative importance of the input features and how this effects the model performance and transferability.

10.8. General Discussion

The research conducted during this PhD project has been largely focused on the fact that the limited storage capacity of most of the poorly productive bedrock aquifers in Ireland limits the amount of groundwater recharge. However, the importance of the aquifer's storage capacity is a current matter of discussion since the resilience of the groundwater resources is affected by the aquifer's capacity to store large volumes of water. Hence, it is not surprising

that the scientific community is looking into improved ways of managing these resources, and enhancing the volumes of stored water through Managed Aquifer Recharge (MAR), as climate change is anticipated to modify the hydrological cycle by an enhancement of the extremes (i.e. more intense rainfall events, longer droughts).

The results obtained from the recharge characterisation have shown that the recharge acceptance of the aquifer is state dependent. Therefore, the volume of water that the aquifer can accept is somehow dependent on the seasonality; the longer the summer recession, then potentially the larger the autumn and winter recharge events. However, it must be borne in mind that the fact that the net recharge is higher in a year with an accentuated seasonality does not imply that there is a larger volume of water available, but that the aquifer has more storage space available because of a previous long recession period.

This has serious implications in terms of groundwater resources management in Ireland, as there is little room for increasing the volumes of groundwater stored as in other regions (i.e. by MAR as presented above), but groundwater levels are most likely going to reach new minimum levels caused by the combination of droughts and increased consumption. Therefore, it is recommended to generally refer to the volume of available groundwater resources as a proportion of the aquifer's maximum capacity when possible. It is for this reason that having an effective S_y value at catchment scale can become useful to assess the available groundwater resources.

Furthermore, the results of forcing the WT-NARX models with the synthetic rainfall series have shown that whereas the groundwater levels present little variation to increased rainfall in winter, any rainfall variation occurring during the dryer months has significant effect because of the reasons presented above. Despite not having a direct effect on the local recharge, this "excess" of water would be released as interflow or overland flow. Where this situation is expected to occur frequently, the aquifer's state should be accounted for in terms of flood forecasting. Additionally, given the importance of the seasonal groundwater fluctuations, the seasonal effect of the large-scale patterns such as the AMO and NAO should also be factored in as it could improve the forecasts.

The application of the wavelet coherence to study the rainfall-groundwater recharge interaction is a powerful and inexpensive method that has revealed important information about the water table dynamics and catchment characteristics. Furthermore, as it represents

the linearity between two signals, it can also provide information beforehand about the performance of a model if one of the signals is used as the predictor and the other as the predictand, as is the case in the WT-NARX models. Similarly, the results obtained by the implementation of the WT-NARX models have demonstrated that these models: (i) are able to capture the relationship between the input variables and (ii) can realistically reproduce the monthly water table dynamics from relatively little information. The two principal challenges identified, namely overfitting and importance of the inputs, could be improved by integrating more robust feature selection methods, and avoiding redundancy by integrating this modelling approach with Information Theory.

The limitations of the WT-NARX models, particularly in their transferability, have been outlined before. However, it is commonly ignored in hydrogeological studies that more “robust” classical models such as the NAM also present transferability issues. The risk is, however, that these limitations are less obvious and consequently, they often go largely unnoticed. For instance, some of the baseflow indices simulated under climate projections are unrealistic based on the knowledge that we have on the catchments. The issue remains that in all climate change impact studies there is the underlying assumption of the stationarity of the parameters in the models implemented. In the case of the NAM, it is the user-defined parameters that dictate the shape of the hydrograph and the proportion of the hydrograph flow components. In the case of the WT-NARX models it is the weights of the input features that determine the relationship between inputs and the objective variable. So far, the only measure that one can take to minimize this effect is to calibrate and validate the models with the largest datasets available in order to capture as much climatic and hydrological variability as possible.

10.9. Future Work

The methods and results presented throughout this thesis are based on local observations and features which, however, are common across Ireland and in many other parts of the world. For this reason, it is considered that they have the potential to be upscaled and/or implemented in other regions.

One of the more direct applications of these results would be to include them in an update of the Irish National Recharge Map. As a first step, a similar approach as the one presented

in Chapter 6 should be implemented in other aquifers to further investigate their storage capacity using groundwater levels records. This would establish the recharge that these aquifers can accept as a function of the groundwater levels rather than based on a fixed recharge amount. Both the application of the water table fluctuation method, and the forcing of the WT-NARX models with different climate inputs have highlighted the role of seasonality on groundwater recharge variability. Hence, it is also recommended to generate a recharge map for each season, as it has been shown that the groundwater table dynamics (and recharge processes) differ substantially from season to season. For instance, high frequency but low magnitude recharge events dominate in winter, when the storage capacity of the aquifers becomes critical. In contrast, at the end of the summer and autumn, after the summer recession, high magnitude recharge events take place refilling the aquifer despite the climate conditions are similar to those in winter.

Given the fact that the national recharge map is a GIS-based tool, there are several possibilities to continue from this point onwards. One of them would be to integrate a reservoir model which would consider the infiltration through the unsaturated zone (i.e. solving Richards equation), and the threshold for interflow generation would be informed by the storage capacity assessed previously. To implement such a model at national scale it would be necessary to first study the surface-groundwater interactions as mentioned above. To do so, the infiltration capacity should be estimated for all the hydrogeological settings represented by the recharge coefficients, so it could represent the whole range of Irish soils and subsoils characteristics.

Furthermore, besides the obvious consequences in terms of water consumption, any changes in the groundwater levels could have a range of serious implications at different scales. For instance, small variations could lead to a deterioration in groundwater dependant ecosystems such as fens or turloughs, as the flora and fauna inhabiting them are sensitive to small groundwater level variations. Hence, further research coupling ecological and groundwater models is necessary in order to protect these species.

This project has focused on how climate change would affect the groundwater resources quantitatively. However, climate change could have a direct impact on groundwater quality as pollutants could reach higher concentrations if a depletion of the groundwater levels occurs. Additionally, the anticipated changes on rainfall patterns and intensity could alter the mobilization of pollutants in the soils.

Moreover, recharge rates are used to delineate source protection areas around springs and wells to protect their zone of contribution against possible polluting activities. In a scenario where, for example, recharge rates decrease, the area of contribution of a given well would increase for a given pumping rate, and its source protection area should be modified accordingly. Therefore, the quantitative aspect of the climate change impact assessment is only an initial step towards the evaluation of all the issues that can derive from climate change. In this way, all the possible impacts stemming from changes in recharge rates need to be addressed in the near future.

As a field in ongoing development, the ANN is the area that logically provides more research lines to pursue. Firstly, because just one specific application has been explored in this thesis, and there are other interesting applications to investigate such as real time monitoring or time-series reconstruction. Secondly, because there is not an established framework nor agreement on an optimal methodology for any of the applications. And lastly, because despite presenting good performances, the ANN methods still present significant opportunities for improvement.

Based on the results obtained during this PhD dissertation, further research efforts would initially focus on developing a solid methodology which would include: (i) a systematic way of selecting the most appropriate input variables, and detail aggregation criteria based on the local hydrogeological characteristics; (ii) further research on the impact of the connection weights and the consequence relative importance of the inputs. This would require the implementation of other methods to contrast with the results obtained by Garson's algorithm, to find the most convenient configuration depending on the application, as well as exploring the possibility of constraining these weights as parameters without affecting the performance of the model; (iii) selecting a best performing network considering its stability and transferability based on the input importance analysis in addition to its performance.

The ANN are *black-box* models with intricate internal structures that complicate the understanding of their underlying principles but, at the same time, they are relatively easy to use and implement without a full understanding of how they work. Therefore, special efforts are required to perfect the application of these models in hydrogeology and environmental sciences in general.

References

- Adamowski J, Chan HF (2011) A wavelet neural network conjunction model for groundwater level forecasting. *J Hydrol* 407:28–40. doi: 10.1016/j.jhydrol.2011.06.013
- Ali I, Bruen M (2016) Methodology and Application of the Combined SWAT-HSPF Model. *Environ Process*. doi: 10.1007/s40710-016-0167-x
- Allen RG, Pereira LS, Raes D, et al (1998a) Chapter 2 - FAO Penman-Monteith equation. *Crop evapotranspiration Guidel Comput Crop water Requir*
- Allen RG, Pereira LS, Raes D, Smith M (1998b) *Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56*. FAO, Rome 300:D05109
- Allen RG, Pruitt WO (1986) Rational use of the FAO Blaney-Criddle formula. *J Irrig Drain Eng*. doi: 10.1061/(ASCE)0733-9437(1986)112:2(139)
- Allen RG, Smith M, Pereira LS, Perrier A (1994) An Update for the Calculation of Reference Evapotranspiration. *ICID Bull*
- Alley WM (2016) Drought-Proofing Groundwater. *Groundwater* 54:309
- Anagnostopoulos GG, Koutsoyiannis D, Christofides A, et al (2010) A comparison of local and aggregated climate model outputs with observed data. *Hydrol Sci J*. doi: 10.1080/02626667.2010.513518
- Andréassian V, Perrin C, Michel C (2004) Impact of imperfect potential evapotranspiration knowledge on the efficiency and parameters of watershed models. *J Hydrol*. doi: 10.1016/j.jhydrol.2003.09.030
- Andreo B, Jiménez P, Durán JJ, et al (2006) Climatic and hydrological variations during the last 117-166 years in the south of the Iberian Peninsula, from spectral and correlation analyses and continuous wavelet analyses. *J Hydrol* 324:24–39. doi: 10.1016/j.jhydrol.2005.09.010
- ANGELINI P (1997) Correlation and spectral analysis of two hydrogeological systems in Central Italy. *Hydrol Sci J*. doi: 10.1080/02626669709492038
- Archbold, M., O'Brein, R., Misstear, B., Gill, L., Deakin, J., Flymm R (2013) *Pathways Project Final Report Volume 2 : Physical Hydrograph Separation and Flow Pathway Modelling*. Environ Prot Agency, Wexford, Irel 2:
- Archbold M, Deakin J, Orr A, et al (2015) *Pathways Project Final Report Volume 1: Field Investigation and Catchment Conceptual Models EPA STRIVE Programme 2007–2013 2007-WQ-CD-1-S1*. Environ Prot Agency, Wexford, Irel

- Archbold M, Deakin J, Orr A, et al (2013) Pathways Project Final Report Volume 1: Field Investigation and Catchment Conceptual Models EPA STRIVE Programme 2007–2013 2007-WQ-CD-1-S1. Environ Prot Agency, Wexford, Irel
- Bair ES (2016) Applied Groundwater Modeling-Simulation of Flow and Advective Transport. Groundwater. doi: 10.1111/gwat.12464
- Barnett FA, Gray ST, Tootle GA (2009) Upper Green River Basin (United States) Streamflow Reconstructions. J Hydrol Eng. doi: 10.1061/(asce)he.1943-5584.0000213
- Barnston AG, Livezey RE (1987) Classification, Seasonality and Persistence of Low-Frequency Atmospheric Circulation Patterns. Mon Weather Rev. doi: 10.1175/1520-0493(1987)115<1083:csapol>2.0.co;2
- Barzegar R, Fijani E, Asghari Moghaddam A, Tziritis E (2017) Forecasting of groundwater level fluctuations using ensemble hybrid multi-wavelet neural network-based models. Sci Total Environ 599–600:20–31. doi: 10.1016/j.scitotenv.2017.04.189
- Basheer IA, Hajmeer M (2000) Artificial neural networks: Fundamentals, computing, design, and application. J Microbiol Methods. doi: 10.1016/S0167-7012(00)00201-3
- Bastola S, Murphy C, Fealy R (2012) Generating probabilistic estimates of hydrological response for Irish catchments using a weather generator and probabilistic climate change scenarios. Hydrol Process 26:2307–2321
- Bates B, Kundzewicz ZW, Wu S, Palutikof J (2008) climate change and Water: technical Paper vi. Intergovernmental Panel on Climate Change (IPCC)
- Berti A, Tardivo G, Chiaudani A, et al (2014) Assessing reference evapotranspiration by the Hargreaves method in north-eastern Italy. Agric Water Manag. doi: 10.1016/j.agwat.2014.03.015
- Beven K (2006) A manifesto for the equifinality thesis. In: Journal of Hydrology
- Beven KJ (2011) Rainfall-runoff modelling: the primer. John Wiley & Sons
- Blaney HF, Criddle WD (1950) Determining water needs from climatological data. USDA Soil Conserv Serv SOS–TP, USA 8–9
- Borsi I, Rossetto R, Schifani C, Hill MC (2013) Modeling unsaturated zone flow and runoff processes by integrating MODFLOW-LGR and VSF, and creating the new CFL package. J Hydrol. doi: 10.1016/j.jhydrol.2013.02.020
- Boughton WC (1984) A simple model for estimating the water yields of ungauged catchments. Civ Engin Trans, I E Aust
- Broderick C, Matthews T, Wilby RL, et al (2016) Transferability of hydrological models and ensemble averaging methods between contrasting climatic periods. Water Resour Res. doi: 10.1002/2016WR018850

- Bueh C, Nakamura H (2007) Scandinavian pattern and its climatic impact. *Q J R Meteorol Soc.* doi: 10.1002/qj.173
- Cai Z, Ofterdinger U (2016) Analysis of groundwater-level response to rainfall and estimation of annual recharge in fractured hard rock aquifers, NW Ireland. *J Hydrol* 535:71–84
- Cassidy R, Comte JC, Nitsche J, et al (2014) Combining multi-scale geophysical techniques for robust hydro-structural characterisation in catchments underlain by hard rock in post-glacial regions. *J Hydrol.* doi: 10.1016/j.jhydrol.2014.06.004
- CDM and OCM (2010a) Well Completion Report - Mattock Catchment, Co. Meath
- CDM and OCM (2010b) Well Completion Report - Dripsey Catchment, Co. Cork
- Chang FJ, Chang LC, Huang CW, Kao IF (2016) Prediction of monthly regional groundwater levels through hybrid soft-computing techniques. *J Hydrol.* doi: 10.1016/j.jhydrol.2016.08.006
- Chapman T, Maxwell A (1996) Baseflow Separation - Comparison of Numerical Methods with Tracer Experiments. In: 23rd Hydrology and Water Resources Symposium. pp 539–545
- Chapman TG (1991) Comment on “Evaluation of automated techniques for base flow and recession analyses” by R. J. Nathan and T. A. McMahon. *Water Resour. Res.*
- Charlier JB, Ladouche B, Maréchal JC (2015) Identifying the impact of climate and anthropic pressures on karst aquifers using wavelet analysis. *J Hydrol* 523:610–623. doi: 10.1016/j.jhydrol.2015.02.003
- Chen D, Gao G, Xu CY, et al (2005) Comparison of the Thornthwaite method and pan data with the standard Penman-Monteith estimates of reference evapotranspiration in China. *Clim Res.* doi: 10.3354/cr028123
- Chinarro D, Villarroel JL, Cuchí JA (2012) Wavelet analysis of Fuenmayor karst spring, San Julián de Banzo, Huesca, Spain. *Environ Earth Sci.* doi: 10.1007/s12665-011-1351-y
- Chinnasamy P, Maheshwari B, Dillon P, et al (2018) Estimation of specific yield using water table fluctuations and cropped area in a hardrock aquifer system of Rajasthan, India. *Agric Water Manag.* doi: 10.1016/j.agwat.2018.02.016
- Chitsazan M, Rahmani G, Neyamadpour A (2015) Forecasting groundwater level by artificial neural networks as an alternative approach to groundwater modeling. *J Geol Soc India* 85:98–106. doi: 10.1007/s12594-015-0197-4
- Chokmani K, Ouarda TBMJ, Hamilton S, et al (2008) Comparison of ice-affected streamflow estimates computed using artificial neural networks and multiple regression techniques. *J Hydrol* 349:383–396. doi: 10.1016/j.jhydrol.2007.11.024
- Coes AL, Spruill TB, Thomasson MJ (2007) Multiple-method estimation of recharge rates at diverse locations in the North Carolina Coastal Plain, USA. *Hydrogeol J* 15:773–788. doi:

10.1007/s10040-006-0123-3

- Comas-Bru L, Mcdermott F (2014) Impacts of the EA and SCA patterns on the European twentieth century NAO-winter climate relationship. *Q J R Meteorol Soc.* doi: 10.1002/qj.2158
- Comte J-C, Cassidy R, Nitsche J, et al (2012) The typology of Irish hard-rock aquifers based on an integrated hydrogeological and geophysical approach. *Hydrogeol J* 20:1569–1588
- Coppola E, Poulton M, Charles E, et al (2003) Application of artificial neural networks to complex groundwater management problems. *Nat Resour Res* 12:303–320
- Cornish CR, Bretherton CS, Percival DB (2006) Maximal overlap wavelet statistical analysis with application to atmospheric turbulence. *Boundary-Layer Meteorol.*
- Coulibaly P, Anctil F, Aravena R, Bobée B (2001) Artificial neural network modeling of water table depth fluctuations. *Water Resour Res.* doi: 10.1029/2000WR900368
- Coulibaly P, Burn DH (2004) Wavelet analysis of variability in annual Canadian streamflows. *Water Resour Res.* doi: 10.1029/2003WR002667
- CPC (2012) Northern Hemisphere Teleconnection Patterns. Climate Prediction Centre, US National Oceanic and Atmospheric Administration
- Crosbie RS, Binning P, Kalma JD (2005) A time series approach to inferring groundwater recharge using the water table fluctuation method. *Water Resour Res* 41:1–9
- Crosbie RS, Dawes WR, Charles SP, et al (2011) Differences in future recharge estimates due to GCMs, downscaling methods and hydrological models. *Geophys Res Lett.* doi: 10.1029/2011GL047657
- Crosbie RS, Pickett T, Mpelasoka FS, et al (2013) An assessment of the climate change impacts on groundwater recharge at a continental scale using a probabilistic approach with an ensemble of GCMs. *Clim Change* 117:41–53
- Cuthbert MO, Tindimugaya C (2010) The importance of preferential flow in controlling groundwater recharge in tropical Africa and implications for modelling the impact of climate change on groundwater resources. *J Water Clim Chang.* doi: 10.2166/wcc.2010.040
- Daliakopoulos IN, Coulibaly P, Tsanis IK (2005) Groundwater level forecasting using artificial neural networks. *J Hydrol* 309:229–240. doi: 10.1016/j.jhydrol.2004.12.001
- Daly, D., Hunter Williams T (2008) Further Characterisation Study An integrated Approach to Quantifying Groundwater and Surface Water Contributions of Stream Flow
- Daly EP (1994) Groundwater resources of the Nore River basin. *Geol Surv Ireland, RS 94:*
- Daly EP (1990) The Likely Effects of Significant Climatic Changes on the Flow Regime in the Principal Irish Aquifers. *Proc 10th Annu Semin Int Assoc Hydrogeol (Irish Group),*

- Dams J, Salvatore E, Van Daele T, et al (2012) Spatio-temporal impact of climate change on the groundwater system. *Hydrol Earth Syst Sci* 16:1517–1531
- Daubechies I (1992) *Ten Lectures of Wavelets*
- David A. Randall RAW (2007) *Climate Models and Their Evaluation*
- Davini P, Cagnazzo C, Neale R, Tribbia J (2012) Coupling between Greenland blocking and the North Atlantic Oscillation pattern. *Geophys Res Lett*. doi: 10.1029/2012GL052315
- Davis SN, Turk LJ (1964) Optimum depth of wells in crystalline rocks. *Ground Water* 2:6–11
- Dawson CW, Wilby RL (2001) Hydrological modelling using artificial neural networks. *Prog Phys Geogr* 25:80–108. doi: 10.1191/030913301674775671
- DELG/EPA/GSI (1999) *Groundwater Protection Schemes*. Department of the Environment and Local Government, Environmental Protection Agency and Geological Survey of Ireland.
- Dickinson JE, Ferré TPA, Bakker M, Crompton B (2014) A screening tool for delineating subregions of steady recharge within groundwater models. *Vadose Zo J*. doi: 10.2136/vzj2013.10.0184
- Dolgonosov BM, Korchagin KA, Kirpichnikova N V. (2008) Modeling of annual oscillations and 1/f-noise of daily river discharges. *J Hydrol* 357:174–187. doi: 10.1016/j.jhydrol.2008.04.023
- Döll P (2009) Vulnerability to the impact of climate change on renewable groundwater resources: a global-scale assessment. *Environ Res Lett* 4:35006
- Döll P, Fiedler K (2008) Global-scale modeling of groundwater recharge. *Hydrol Earth Syst Sci*. doi: 10.5194/hess-12-863-2008
- Doody DG, Archbold M, Foy RH, Flynn R (2012) Approaches to the implementation of the Water Framework Directive: Targeting mitigation measures at critical source areas of diffuse phosphorus in Irish catchments. *J. Environ. Manage.*
- Draper NR, Smith H (1998) *Applied regression analysis*. John Wiley & Sons
- Drew DP (2008) Hydrogeology of lowland karst in Ireland. *Q J Eng Geol Hydrogeol* 41:61–72
- Ebrahimi H, Rajaei T (2017) Simulation of groundwater level variations using wavelet combined with neural network, linear regression and support vector machine. *Glob Planet Change* 148:181–191. doi: 10.1016/j.gloplacha.2016.11.014
- Eckhardt K (2005) How to construct recursive digital filters for baseflow separation. *Hydrol Process* 19:507–515. doi: 10.1002/hyp.5675
- Eckhardt K (2012) Technical note: Analytical sensitivity analysis of a two parameter recursive digital baseflow separation filter. *Hydrol Earth Syst Sci* 16:451–455. doi: 10.5194/hess-

- Efroymson M. (1960) Multiple Regression Analysis. Mathematical Methods for Digital Computers
- EU Water Framework Directive EU Water Framework Directive - Directive 2000/60/EC of the European Parliament and of the Council establishing a framework for the Community action in the field of water policy. Official Journal of the European Communities, L327, Brussels, Belgium
- Falzo S, Gleeson E, Lambkin K, et al (2019) Analysis of the severe drought in Ireland in 2018. *Weather* 74:368–373
- Fang Z-F. (2004) Statistical relationship between the northern hemisphere sea ice and atmospheric circulation during winter time. *Obs Theory Model Atmos Var World Sci Ser Meteorol East Asia* 131–141
- Fitzsimons, V .; Daly. D.; Wright, G.; Hunter-Williams T (2005) Rock type versus fractures-current understanding of Irish aquifers. In: *Groundwater in Ireland:Proceedings of the International Association of Hydrogeologists (Irish Group) 25th Anniversary conference, Tullamore.* pp 17–28
- Fitzsimons VP, Misstear BDR (2006) Estimating groundwater recharge through tills: a sensitivity analysis of soil moisture budgets and till properties in Ireland. *Hydrogeol J* 14:548–561
- Fleming SW, Marsh Lavenue A, Aly AH, Adams A (2002) Practical applications of spectral analysis of hydrologic time series. *Hydrol Process.* doi: 10.1002/hyp.523
- Fourier J (1822) Joseph fourier, *théorie analytique de la chaleur* (1822). In: *Landmark Writings in Western Mathematics 1640-1940*
- Furtado JC, Di Lorenzo E, Schneider N, Bond NA (2011) North pacific decadal variability and climate change in the IPCC AR4 models. *J Clim.* doi: 10.1175/2010JCLI3584.1
- Gabor D (1946) Theory of communication. Part 1: The analysis of information. *J Inst Electr Eng - Part III Radio Commun Eng.* doi: 10.1049/ji-3-2.1946.0074
- Garson GD (1991) A comparison of neural network and expert systems algorithms with common multivariate procedures for analysis of social science data. *Soc Sci Comput Rev* 9:399–434
- Ge Y, Gong G (2009) North American snow depth and climate teleconnection patterns. *J Clim* 22:217–233
- George H. Hargreaves, Zohrab A. Samani (1985) Reference Crop Evapotranspiration from Temperature. *Appl Eng Agric.* doi: 10.13031/2013.26773
- Gevrey M, Dimopoulos I, Lek S (2003) Review and comparison of methods to study the

- contribution of variables in artificial neural network models. In: Ecological Modelling
- Ghil M, Allen MR, Dettinger MD, et al (2002) Advanced spectral methods for climatic time series. *Rev Geophys*. doi: 10.1029/2000RG000092
- Gill LW, Naughton O, Johnston PM (2013a) Modeling a network of turloughs in lowland karst. *Water Resour Res*. doi: 10.1002/wrcr.20299
- Gill LW, Naughton O, Johnston PM, et al (2013b) Characterisation of hydrogeological connections in a lowland karst network using time series analysis of water levels in ephemeral groundwater-fed lakes (turloughs). *J Hydrol*. doi: 10.1016/j.jhydrol.2013.07.002
- Gleeson E, McGrath R, Treanor M (2013) Ireland's climate: the road ahead. Met Éireann
- Goh ATC (1995) Back-propagation neural networks for modeling complex systems. *Artif Intell Eng*. doi: 10.1016/0954-1810(94)00011-S
- Gong G, Wang L, Condon L, et al (2010) A Simple framework for incorporating seasonal streamflow forecasts into existing water resource management practices1. *J Am Water Resour Assoc*. doi: 10.1111/j.1752-1688.2010.00435.x
- Govindaraju RS (2000) Artificial neural networks in hydrology. I: Preliminary concepts. *J Hydrol Eng*. doi: 10.1061/(ASCE)1084-0699(2000)5:2(115)
- Green HW, Ampt GA (1911) Studies on soil physics: Flow of air and water through soils. *J Aric Sci*
- Green TR, Taniguchi M, Kooi H, et al (2011) Beneath the surface of global change: Impacts of climate change on groundwater. *J Hydrol* 405:532–560
- Gregor M (2010) Software Package for Water Sciences BFI+ 3.0 User's Manual
- Grinsted A, Moore JC, Jevrejeva S (2004) Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear Process Geophys* 11:561–566. doi: 10.5194/npg-11-561-2004
- Gupta H V., Kling H, Yilmaz KK, Martinez GF (2009) Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *J Hydrol*. doi: 10.1016/j.jhydrol.2009.08.003
- Gurdak JJ, Hanson RT, Green RT (2009) Effects of climate variability and change on groundwater resources of the United States. *US Geol Surv Fact Sheet*
- Guzman SM, Paz JO, Tagert MLM (2017) The Use of NARX Neural Networks to Forecast Daily Groundwater Levels. *Water Resour Manag* 31:1591–1603. doi: 10.1007/s11269-017-1598-5
- Hagemann S, Chen C, Haerter JO, et al (2011) Impact of a statistical bias correction on the projected hydrological changes obtained from three GCMs and two hydrology models.

- Hall M (2006) Resolution and uncertainty in spectral decomposition. *First Break*
- Hanna E, Hall RJ, Cropper TE, et al (2018) Greenland blocking index daily series 1851–2015: Analysis of changes in extremes and links with North Atlantic and UK climate variability and change. *Int J Climatol*. doi: 10.1002/joc.5516
- Hanson RT, Dettinger MD, Newhouse MW (2006) Relations between climatic variability and hydrologic time series from four alluvial basins across the southwestern United States. *Hydrogeol J*. doi: 10.1007/s10040-006-0067-7
- Hanson RT, Newhouse MW, Dettinger MD (2004) A methodology to assess relations between climatic variability and variations in hydrologic time series in the southwestern United States. *J Hydrol*. doi: 10.1016/j.jhydrol.2003.10.006
- Hao Y, Liu G, Li H, et al (2012) Investigation of karstic hydrological processes of Niangziguan Springs (North China) using wavelet analysis. *Hydrol Process*. doi: 10.1002/hyp.8265
- Hardy HH, Beier RA (1994) *Fractals in reservoir engineering*. World Scientific
- Hargreaves GH, Samani ZA (1985) Reference crop evapotranspiration from temperature. *Appl Eng Agric* 1:96–99
- Hartmann A, Lange J, Vivó Aguado À, et al (2012) A multi-model approach for improved simulations of future water availability at a large Eastern Mediterranean karst spring. *J Hydrol*. doi: 10.1016/j.jhydrol.2012.08.024
- Hartmann G, Bárdossy A (2005) Investigation of the transferability of hydrological models and a method to improve model calibration. *Adv Geosci*. doi: 10.5194/adgeo-5-83-2005
- Haykin S (1999) *Neural networks: a comprehensive foundation*. *Knowl Eng Rev*. doi: 10.1017/S0269888998214044
- Hazeleger W, Van Den Hurk BJM, Min E, et al (2015) Tales of future weather. *Nat Clim Chang*. doi: 10.1038/nclimate2450
- Healy RW (2010) *Estimating groundwater recharge*. Cambridge University Press
- Healy RW, Cook PG (2002) Using groundwater levels to estimate recharge. *Hydrogeol J* 10:91–109. doi: 10.1007/s10040-001-0178-0
- Heisenberg W (1927) Über den anschaulichen Inhalt der quantentheoretischen Kinematik und Mechanik. *Zeitschrift für Phys*. doi: 10.1007/BF01397280
- Hocking RR (1976) *The Analysis and Selection of Variables in Linear Regression*. *Biometrics*. doi: 10.2307/2529336
- Holman IP (2006) Climate change impacts on groundwater recharge-uncertainty, shortcomings, and the way forward? *Hydrogeol J*. doi: 10.1007/s10040-005-0467-0
- Holman IP, Allen DM, Cuthbert MO, Goderniaux P (2012) Towards best practice for assessing

- the impacts of climate change on groundwater. *Hydrogeol J* 20:1–4
- Holman IP, Rivas-Casado M, Bloomfield JP, Gurdak JJ (2011) Identifying non-stationary groundwater level response to North Atlantic ocean-atmosphere teleconnection patterns using wavelet coherence. *Hydrogeol J*. doi: 10.1007/s10040-011-0755-9
- Holman IP, Rivas-Casado M, Howden NJK, et al (2009) Linking North Atlantic ocean-atmosphere teleconnection patterns and hydrogeological responses in temperate groundwater systems. *Hydrol. Process.*
- Hulme P, Rushton K, Fletcher S (2001) Estimating recharge in UK catchments. *IAHS Publ* 33–42
- Hunter Williams, T., Tedd, K., Kelly C (2019) Groundwater Storage and Transmission in Irish Aquifers Implications For Yield Sustainability. In: *Groundwater: droughts, floods and climate change. Proceedingx of the 39th Annual Groundwater Conference, International Associatiion of Hydrogeologists (Irish Group)*
- Hunter Williams NH, Missteart BDR, Daly D, Lee M (2013) Development of a national groundwater recharge map for the Republic of Ireland. *Q J Eng Geol Hydrogeol* 46:493–506
- Hurrell JW (1995) Decadal trends in the North Atlantic oscillation: Regional temperatures and precipitation. *Science* (80-). doi: 10.1126/science.269.5224.676
- Ibrahim OM (2013) A comparison of methods for assessing the relative importance of input variables in artificial neural networks. *J Appl Sci Res*. doi: 10.1067/mmt.2002.123333
- Institute of Hydrology (1980) Low flow studies. *Inst Hydrol* 1:. doi: 10.1017/CBO9781107415324.004
- IPCC (2007) *Climate Change 2007: impacts, adaptation and vulnerability: contribution of Working Group II to the fourth assessment report of the Intergovernmental Panel on Climate Change*. Cambridge University Press
- IPCC, Stocker TF, Qin D, et al (2013) *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA
- IWGGW Risk Assessment compilation. Irish Working Group on Groundwater, Guidance Document, GW8.
- Izady A, Davary K, Alizadeh A, et al (2013) Application of NN-ARX Model to Predict Groundwater Levels in the Neishaboor Plain, Iran. *Water Resour Manag*. doi: 10.1007/s11269-013-0432-y
- Jiménez-Martínez J, Longuevergne L, Le Borgne T, et al (2013) Temporal and spatial scaling

- of hydraulic response to recharge in fractured aquifers: Insights from a frequency domain analysis. *Water Resour Res.* doi: 10.1002/wrcr.20260
- Jolliffe IT (1986) *Principal Component Analysis and Factor Analysis*
- Jolliffe IT (2002) *Principal Component Analysis, Second Edition.* *Encycl Stat Behav Sci.* doi: 10.2307/1270093
- Jordan P, Menary W, Daly K, et al (2005) Patterns and processes of phosphorus transfer from Irish grassland soils to rivers - Integration of laboratory and catchment studies. *J Hydrol.* doi: 10.1016/j.jhydrol.2004.07.021
- Kay AL, Davies HN (2008) Calculating potential evaporation from climate model data: a source of uncertainty for hydrological climate change impacts. *J Hydrol* 358:221–239
- Kelly C, Hunter Williams T, Missteart BM, Motherway K (2015) *Irish Aquifer Properties – A reference manual guide.* Prepared on behalf of the Geological Survey of Ireland and the Environmental Protection Agency.
- Khalil B, Broda S, Adamowski J, et al (2015) Short-term forecasting of groundwater levels under conditions of mine-tailings recharge using wavelet ensemble neural network models. *Hydrogeol J.* doi: 10.1007/s10040-014-1204-3
- Kidmose J, Refsgaard JC, Trolborg L, et al (2013) Climate change impact on groundwater levels: ensemble modelling of extreme values. *Hydrol Earth Syst Sci*
- Kiely G, Leahy P, Fenton M, Donovan (2008) Flood studies update programme work group 3. Flood hydrograph analysis work package 3.2 Flood Event Analysis- OPW Report
- King AC, Raiber M, Cox ME, Cendón DI (2017) Comparison of groundwater recharge estimation techniques in an alluvial aquifer system with an intermittent/ephemeral stream (Queensland, Australia). *Hydrogeol J* 25:1759–1777. doi: 10.1007/s10040-017-1565-5
- Kingston DG, Todd MC, Taylor RG, et al (2009) Uncertainty in the estimation of potential evapotranspiration under climate change. *Geophys Res Lett.* doi: 10.1029/2009GL040267
- Knappe J (2019) *The influence of a growing microbial biomat on water retention and pollutant attenuation in soil treatment units receiving domestic effluent.* University of Limerick
- Knight JR, Folland CK, Scaife AA (2006) Climate impacts of the Atlantic multidecadal oscillation. *Geophys Res Lett.* doi: 10.1029/2006GL026242
- Knutti R, Masson D, Gettelman A (2013) Climate model genealogy: Generation CMIP5 and how we got there. *Geophys Res Lett.* doi: 10.1002/grl.50256
- Kumar P, Foufoula-Georgiou E (1997) Wavelet analysis for geophysical applications. *Rev*

- Geophys. doi: 10.1029/97RG00427
- Kundzewicz ZW, Stakhiv EZ (2010) Are climate models “ready for prime time” in water resources management applications, or is more research needed? *Hydrol Sci J* 55:1085–1089. doi: 10.1080/02626667.2010.513211
- Kurylyk BL, MacQuarrie KTB (2013) The uncertainty associated with estimating future groundwater recharge: A summary of recent research and an example from a small unconfined aquifer in a northern humid-continental climate. *J Hydrol* 492:244–253
- Kuss AJM, Gurdak JJ (2014) Groundwater level response in U.S. principal aquifers to ENSO, NAO, PDO, and AMO. *J Hydrol*. doi: 10.1016/j.jhydrol.2014.09.069
- Labat D (2005) Recent advances in wavelet analyses: Part 1. A review of concepts. *J Hydrol*. doi: 10.1016/j.jhydrol.2005.04.003
- Labat D, Ababou R, Mangin A (2000a) Rainfall-runoff relations for karstic springs. Part II: Continuous wavelet and discrete orthogonal multiresolution analyses. *J Hydrol* 238:149–178. doi: 10.1016/S0022-1694(00)00322-X
- Labat D, Ababou R, Mangin A (2000b) Rainfall-runoff relations for karstic springs. Part I: Convolution and spectral analyses. *J Hydrol* 238:123–148. doi: 10.1016/S0022-1694(00)00321-8
- Lachassagne P, Wyns R, Dewandel B (2011) The fracture permeability of Hard Rock Aquifers is due neither to tectonics, nor to unloading, but to weathering processes. *Terra Nov.*
- Lallahem S, Mania J, Hani A, Najjar Y (2005) On the use of neural networks to evaluate groundwater levels in fractured media. *J Hydrol* 307:92–111. doi: 10.1016/j.jhydrol.2004.10.005
- Lang D, Zheng J, Shi J, et al (2017) A comparative study of potential evapotranspiration estimation by eight methods with FAO Penman–Monteith method in southwestern China. *Water (Switzerland)*. doi: 10.3390/w9100734
- Lapp SL, St. Jacques JM, Barrow EM, Sauchyn DJ (2012) GCM projections for the Pacific Decadal Oscillation under greenhouse forcing for the early 21st century. *Int J Climatol*. doi: 10.1002/joc.2364
- Lark RM, Webster R (2001) Changes in variance and correlation of soil properties with scale and location: Analysis using an adapted maximal overlap discrete wavelet transform. *Eur J Soil Sci*. doi: 10.1046/j.1365-2389.2001.00420.x
- Larocque M, Mangin A, Razack M, Banton O (1998) Contribution of correlation and spectral analyses to the regional study of a large karst aquifer (Charente, France). *J Hydrol*. doi: 10.1016/S0022-1694(97)00155-8
- Lavers DA, Hannah DM, Bradley C (2015) Connecting large-scale atmospheric circulation,

- river flow and groundwater levels in a chalk catchment in southern England. *J Hydrol*. doi: 10.1016/j.jhydrol.2015.01.060
- Lawrence S, Giles CL (2002) Overfitting and neural networks: conjugate gradient and backpropagation. 114–119 vol.1. doi: 10.1109/ijcnn.2000.857823
- Lee JY, Lee KK (2000) Use of hydrologic time series data for identification of recharge mechanism in a fractured bedrock aquifer system. *J Hydrol* 229:190–201. doi: 10.1016/S0022-1694(00)00158-X
- Lee JY, Yi MJ, Hwang D (2005) Dependency of hydrologic responses and recharge estimates on water-level monitoring locations within a small catchment. *Geosci J*. doi: 10.1007/BF02910588
- Lerner DN, Issar AS, Simmers I (1990) Groundwater recharge: a guide to understanding and estimating natural recharge. Heise Hannover
- Leterme B, Mallants D, Jacques D (2012) Sensitivity of groundwater recharge using climatic analogues and HYDRUS-1D. *Hydrol Earth Syst Sci*. doi: 10.5194/hess-16-2485-2012
- Little MA, Bloomfield JP (2010) Robust evidence for random fractal scaling of groundwater levels in unconfined aquifers. *J Hydrol* 393:362–369. doi: 10.1016/j.jhydrol.2010.08.031
- Lu J, Sun G, McNulty SG, Amatya DM (2005) A comparison of six potential evapotranspiration methods for regional use in the southeastern United States¹
- Lyne VD, Hollick M (1979) Stochastic time-variable rainfall-runoff modelling. In: *Hydrology and Water Resources Symposium*. pp 89–92
- Ma Y, Feng S, Su D, et al (2010) Modeling water infiltration in a large layered soil column with a modified Green-Ampt model and HYDRUS-1D. *Comput Electron Agric*. doi: 10.1016/j.compag.2009.07.006
- Machiwal D, Jha MK (2015) GIS-based water balance modeling for estimating regional specific yield and distributed recharge in data-scarce hard-rock regions. *J Hydro-Environment Res*. doi: 10.1016/j.jher.2014.07.004
- Madsen H (2000) Automatic calibration of a conceptual rainfall-runoff model using multiple objectives. *J Hydrol*. doi: 10.1016/S0022-1694(00)00279-1
- Mallat SG (1989) A Theory for Multiresolution Signal Decomposition: The Wavelet Representation. *IEEE Trans Pattern Anal Mach Intell*. doi: 10.1109/34.192463
- Mangin A (1984) The use of autocorrelation and spectral analyses to obtain a better understanding of hydrological systems. *J Hydrol*
- Maréchal JC, Dewandel B, Ahmed S, et al (2006) Combined estimation of specific yield and natural recharge in a semi-arid groundwater basin with irrigated agriculture. *J Hydrol*. doi: 10.1016/j.jhydrol.2006.02.022

- Massei N, Laignel B, Deloffre J, et al (2010) Long-term hydrological changes of the Seine River flow (France) and their relation to the North Atlantic Oscillation over the period 1950-2008. *Int J Climatol*. doi: 10.1002/joc.2022
- Mathevet T, Lepiller M I., Mangin A (2010) Application of time-series analyses to the hydrological functioning of an Alpine karstic system: the case of Bange-L'Eau-Morte. *Hydrol Earth Syst Sci* 8:1051–1064. doi: 10.5194/hess-8-1051-2004
- Mau DP, Winter TC (1997) Estimating Ground-Water Recharge from Streamflow Hydrographs for a Small Mountain Watershed in a Temperate Humid Climate, New Hampshire, USA. *Groundwater*
- McCarthy M, Spillane S, Walsh S, Kendon M (2016) The meteorology of the exceptional winter of 2015/2016 across the UK and Ireland. *Weather* 71:305–313
- McElwain L, Sweeney J (2007) Key meteorological indicators of climate change in Ireland. Environmental Protection Agency Johnstown Castle, Wexford, Ireland
- McMahon TA, Finlayson BL, Peel MC (2016) Historical developments of models for estimating evaporation using standard meteorological data. *Wiley Interdiscip Rev Water*. doi: 10.1002/wat2.1172
- Merz R, Parajka J, Blöschl G (2011) Time stability of catchment model parameters: Implications for climate impact analyses. *Water Resour Res*. doi: 10.1029/2010WR009505
- Merz S., Murphy R, Graszewicz Z, et al (2009) Australia Rainfall and Runoff Revision Project 7: Baseflow for Catchment Simulation - Selection Approach
- Meyer Y (1992) *Wavelets and applications*. Masson Paris
- Milla K, Kish S (2006) A low-cost microprocessor and infrared sensor system for automating water infiltration measurements. *Comput Electron Agric*. doi: 10.1016/j.compag.2006.05.001
- Milly PCD, Betancourt J, Falkenmark M, et al (2008) Stationarity Is Dead: Whither Water Management? *Science* (80-) 319:573 LP – 574. doi: 10.1126/science.1151915
- Missteart B, Banks D, Clark L (2017) Water Wells and Boreholes
- Missteart BDR, Brown L, Daly D (2009a) A methodology for making initial estimates of groundwater recharge from groundwater vulnerability mapping. *Hydrogeol J* 17:275–285
- Missteart BDR, Brown L, Johnston PM (2009b) Estimation of groundwater recharge in a major sand and gravel aquifer in Ireland using multiple approaches. *Hydrogeol J* 17:693–706
- Missteart BDR, Brown L, Williams NH (2008) Groundwater recharge to a fractured limestone aquifer overlain by glacial till in County Monaghan, Ireland. *Q J Eng Geol Hydrogeol*

- Missteart BDR, Fitzsimons V (2007) Estimating groundwater recharge in fractured bedrock aquifers in Ireland. *Groundw Fract Rocks* 243–257
- Moe H, Craig M, Daly D (2010) Poorly productive aquifers: monitoring installations and conceptual understanding. CDM Environ Prot Agency, Dublin
- Moe H, Daly D, Hunter-Williams N, et al (2007) A national assessment of groundwater abstraction pressures. *Groundw Oppor Press*
- Moeck C, Brunner P, Hunkeler D (2016) The influence of model structure on groundwater recharge rates in climate-change impact studies. *Hydrogeol J*. doi: 10.1007/s10040-016-1367-1
- Moore GWK, Renfrew IA (2012) Cold European winters: Interplay between the NAO and the East Atlantic mode. *Atmos Sci Lett*. doi: 10.1002/asl.356
- Murphy C, Charlton R (2006) Climate Change Impact on Catchment Hydrology & Water Resources for Selected Catchments in Ireland
- Murphy C, Wilby RL, Matthews T, et al (2020) The forgotten drought of 1,765–1,768: Reconstructing and re-evaluating historical droughts in the British and Irish Isles. *Int J Climatol*. doi: 10.1002/joc.6521
- Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models part I — A discussion of principles. *J Hydrol*. doi: 10.1016/0022-1694(70)90255-6
- Nathan RJ, McMahon TA (1990) Evaluation of automated techniques for base flow and recession analyses. *Water Resour Res* 26:1465–1473. doi: 10.1029/WR026i007p01465
- Naughton O, Johnston PM, Gill LW (2012) Groundwater flooding in Irish karst: The hydrological characterisation of ephemeral lakes (turloughs). *J Hydrol*. doi: 10.1016/j.jhydrol.2012.08.012
- Neves MC, Jerez S, Trigo RM (2019) The response of piezometric levels in Portugal to NAO, EA, and SCAND climate patterns. *J Hydrol*. doi: 10.1016/j.jhydrol.2018.11.054
- Nielsen SA, Hansen E (1973) Numerical simulation fo the rainfall- runoff process on a daily basis. *Hydrol Res* 4:171–190. doi: 10.2166/nh.1973.0013
- O’Brien RJ (2013) Modelling of Hydrological Pathways in Irish Catchments. Trinity College
- O’Brien RJ, Missteart BD, Gill LW, et al (2013a) Developing an integrated hydrograph separation and lumped modelling approach to quantifying hydrological pathways in Irish river catchments. *J Hydrol*. doi: 10.1016/j.jhydrol.2013.01.034
- O’Brien RJ, Missteart BD, Gill LW, et al (2013b) Developing an integrated hydrograph separation and lumped modelling approach to quantifying hydrological pathways in Irish river catchments. *J Hydrol* 486:259–270

- Olden JD, Jackson DA (2002) Illuminating the “black box”: A randomization approach for understanding variable contributions in artificial neural networks. *Ecol Modell.* doi: 10.1016/S0304-3800(02)00064-9
- Olden JD, Joy MK, Death RG (2004) An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. *Ecol Modell.* doi: 10.1016/j.ecolmodel.2004.03.013
- Oudin L, Hervieu F, Michel C, et al (2005) Which potential evapotranspiration input for a lumped rainfall-runoff model? Part 2 - Towards a simple and efficient potential evapotranspiration model for rainfall-runoff modelling. *J Hydrol.* doi: 10.1016/j.jhydrol.2004.08.026
- Padilla A, Pulido-Bosch A (1995) Study of hydrographs of karstic aquifers by means of correlation and cross-spectral analysis. *J Hydrol.* doi: 10.1016/0022-1694(94)02648-U
- Peña-Arancibia JL, Van Dijk AIJM, Mulligan M, Bruijnzeel LA (2010) The role of climatic and terrain attributes in estimating baseflow recession in tropical catchments. *Hydrol Earth Syst Sci.* doi: 10.5194/hess-14-2193-2010
- Percival DB, Guttorp P (1994) Long-Memory Processes, the Allan Variance and Wavelets. In: *Wavelet Analysis and Its Applications*
- Percival DB, Walden AT (2006) *Wavelet methods for time series analysis.* Cambridge university press
- Perez-Valdivia C, Sauchyn D, Vanstone J (2012) Groundwater levels and teleconnection patterns in the Canadian Prairies. *Water Resour Res.* doi: 10.1029/2011WR010930
- Pfletschinger H, Prömmel K, Schüth C, et al (2014) Sensitivity of Vadose zone water fluxes to climate shifts in arid settings. *Vadose Zo J.* doi: 10.2136/vzj2013.02.0043
- Piotrowski AP, Napiorkowski JJ (2013) A comparison of methods to avoid overfitting in neural networks training in the case of catchment runoff modelling. *J Hydrol* 476:97–111. doi: 10.1016/j.jhydrol.2012.10.019
- Prechelt L (1998) Automatic Early Stopping Using Cross Validation : Quantifying the Criteria
1 Training for generalization 2 Ideal and real generalization curves. *Neural Networks* 11:1–12
- Priestley, Taylor (1972) On the assessment of surface heat flux and evaporation using large scale parameters. In: *Mon. Weather Rev.* Citeseer
- Quilty J, Adamowski J (2018) Addressing the incorrect usage of wavelet-based hydrological and water resources forecasting models for real-world applications with best practices and a new forecasting framework. *J Hydrol.* doi: 10.1016/j.jhydrol.2018.05.003
- Radcliffe DE, Šimůnek J (2010) *Soil physics with HYDRUS: Modeling and applications*

- Rajaei T, Ebrahimi H, Nourani V (2019) A review of the artificial intelligence methods in groundwater level modeling. *J. Hydrol.*
- Raposo JR, Dafonte J, Molinero J (2013) Assessing the impact of future climate change on groundwater recharge in Galicia-Costa, Spain. *Hydrogeol J* 21:459–479
- Richards LA (1931) Capillary conduction of liquids through porous mediums. *J Appl Phys.* doi: 10.1063/1.1745010
- Risser DW, Gburek WJ, Folmar GJ (2005) Comparison of methods for estimating groundwater recharge and base flow at a small watershed underlain by fractured bedrock in the eastern United States. US Department of the Interior, US Geological Survey
- Ropelewski CF, Halpert MS (1987) Global and Regional Scale Precipitation Patterns Associated with the El Niño/Southern Oscillation. *Mon Weather Rev.* doi: 10.1175/1520-0493(1987)115<1606:garspp>2.0.co;2
- RPS (2008) Further Characterisation Study: An integrated Approach to Quantifying Groundwater and Surface Water Contributions of Stream Flow
- Rust W, Holman I, Corstanje R, et al (2018) A conceptual model for climatic teleconnection signal control on groundwater variability in Europe. *Earth-Science Rev.*
- Ruud N, Harter T, Naugle A (2004) Estimation of groundwater pumping as closure to the water balance of a semi-arid, irrigated agricultural basin. *J Hydrol.* doi: 10.1016/j.jhydrol.2004.04.014
- Saco P, Kumar P (2000) Coherent modes in multiscale variability of streamflow over the United States. *Water Resour Res.* doi: 10.1029/1999WR900345
- Sánchez-Vila X, Carrera J, Girardi JP (1996) Scale effects in transmissivity. *J Hydrol.* doi: 10.1016/S0022-1694(96)80031-X
- Sang YF, Wang D, Wu JC, et al (2009) Entropy-based wavelet de-noising method for time series analysis. *Entropy.* doi: 10.3390/e11041123
- Scaife AA, Arribas A, Blockley E, et al (2014) Skillful long-range prediction of European and North American winters. *Geophys Res Lett.* doi: 10.1002/2014GL059637
- Scanlon BR, Healy RW, Cook PG (2002) Choosing appropriate techniques for quantifying groundwater recharge. *Hydrogeol J* 10:18–39
- Schittenkopf C, Deco G, Brauer W (1997) Two strategies to avoid overfitting in feedforward networks. *Neural Networks* 10:505–516. doi: 10.1016/S0893-6080(96)00086-X
- Schnarr E, Trzaska S (2014) A review of downscaling methods for climate change projections. United States Agency Int Dev by Tetra Tech ARD 1–42
- Schulte RP, Diamond J, Finkle K, et al (2005) Predicting the soil moisture conditions of Irish grasslands

- Seguí PQ, Ribes A, Martin E, et al (2010) Comparison of three downscaling methods in simulating the impact of climate change on the hydrology of Mediterranean basins. *J Hydrol* 383:111–124
- Shannon CE (1948) A Mathematical Theory of Communication. *Bell Syst Tech J.* doi: 10.1002/j.1538-7305.1948.tb01338.x
- Shepherd TG (2016) A Common Framework for Approaches to Extreme Event Attribution. *Curr. Clim. Chang. Reports*
- Shepherd TG, Boyd E, Calel RA, et al (2018) Storylines: an alternative approach to representing uncertainty in physical aspects of climate change. *Clim Change.* doi: 10.1007/s10584-018-2317-9
- Shiklomanov I a. (1998) World Water Resources. A new appraisal and assessment for the 21st century. United Nations Educ Sci Cult Organ
- Simunek J, Sejna M, Saito H, et al (2009) “The HYDRUS-1D software package for simulating the one-dimensional movement of water, heat, and multiple solutes in variably-saturated media. Version 4.08. HYDRUS Softw. Ser. 3.
- Simunek J, van Genuchten MT, Sejna M (2012) HYDRUS: Model use, calibration, and validation. *Trans Am Soc Agric Biol Eng.* doi: 10.1029/2002WR001340; Bradford, S.A., Šimůnek, J., Bettehar, M., Van, G.M.Th., Yates, S.R., Modeling colloid attachment, straining, and exclusion in saturated porous media (2003) *Environ. Sci. Tech.*, 37 (10), pp. 2242-2250; Bradford, S.A., Bettehar, M., Šimůnek, J., Van Genuchten, M.Th., Straining and attachment of colloids in physically heterogeneous porous media (2004) *Vadose Zone J.*, 3 (2), pp. 384-394; Brooks, R.H., Corey, A.T., (1964) Hydraulic Properties of Porous Media, , Hydrology Paper
- Šimůnek J, Weihermüller L (2018) Using HYDRUS-1D to Simulate Infiltration. 8
- Sivakumar B (2016) Chaos in hydrology: bridging determinism and stochasticity. Springer
- Sloto R a., Crouse MY (1996) Hysep: a computer program for streamflow hydrograph separation and analysis. US Geol Surv Water-Resources Investig Rep 96-4040 54
- Smith LC, Turcotte DL, Isacks BL (1998) Stream flow characterization and feature detection using a discrete wavelet transform. *Hydrol Process.* doi: 10.1002/(SICI)1099-1085(199802)12:2<233::AID-HYP573>3.0.CO;2-3
- Sophocleous MA (1991) Combining the soilwater balance and water-level fluctuation methods to estimate natural groundwater recharge: Practical aspects. *J Hydrol.* doi: 10.1016/0022-1694(91)90016-B
- Srivastava N, Hinton G, Krizhevsky A, et al (2014) Dropout: A simple way to prevent neural networks from overfitting. *J Mach Learn Res*

- Ssegane H, Tollner EW, Mohamoud YM, et al (2012a) Advances in variable selection methods I: Causal selection methods versus stepwise regression and principal component analysis on data of known and unknown functional relationships. *J Hydrol* 438–439:16–25. doi: 10.1016/j.jhydrol.2012.01.008
- Ssegane H, Tollner EW, Mohamoud YM, et al (2012b) Advances in variable selection methods II: Effect of variable selection method on classification of hydrologically similar watersheds in three Mid-Atlantic ecoregions. *J Hydrol* 438–439:26–38. doi: 10.1016/j.jhydrol.2012.01.035
- Steele-Dunne S, Lynch P, McGrath R, et al (2008) The impacts of climate change on hydrology in Ireland. *J Hydrol* 356:28–45
- Stephenson DB, Pavan V, Collins M, et al (2006) North Atlantic Oscillation response to transient greenhouse gas forcing and the impact on European winter climate: A CMIP2 multi-model assessment. *Clim Dyn*. doi: 10.1007/s00382-006-0140-x
- Stone J (1997) Climate change 1995: The science of climate change. Contribution of working group I to the second assessment report of the intergovernmental panel on climate change. *Glob Environ Chang*. doi: 10.1016/s0959-3780(97)82913-5
- Stoner AMK, Hayhoe K, Wuebbles DJ (2009) Assessing general circulation model simulations of atmospheric teleconnection patterns. *J Clim*. doi: 10.1175/2009JCLI2577.1
- Sulzbacher H, Wiederhold H, Siemon B, et al (2012) Numerical modelling of climate change impacts on freshwater lenses on the North Sea Island of Borkum using hydrological and geophysical methods. *Hydrol Earth Syst Sci* 16:3621–3643
- Sun Y, Wendi D, Kim DE, Liong SY (2016) Technical note: Application of artificial neural networks in groundwater table forecasting-a case study in a Singapore swamp forest. *Hydrol Earth Syst Sci*. doi: 10.5194/hess-20-1405-2016
- Sutton RT, Hodson DLR (2005) Ocean science: Atlantic Ocean forcing of North American and European summer climate. *Science* (80-). doi: 10.1126/science.1109496
- Swartz M, Misstear BDR, Daly D, Farrell ER (2003) Assessing subsoil permeability for groundwater vulnerability. *Q J Eng Geol Hydrogeol* 36:173–184
- Sweeney J, Albanito F, Brereton A, et al (2008) Climate Change–Refining the Impacts for Ireland: STRIVE Report (2001-CD-C3-M1) ISBN: 978-1-84095-297-1
- Taormina R, Chau KW, Sethi R (2012) Artificial neural network simulation of hourly groundwater levels in a coastal aquifer system of the Venice lagoon. *Eng Appl Artif Intell*. doi: 10.1016/j.engappai.2012.02.009
- Taylor RG, Scanlon B, Döll P, et al (2013) Ground water and climate change. *Nat Clim Chang* 3:322–329

- Tedd KM, Hunter Williams NH, Kelly C Towards calculating national annual average deep and shallow groundwater throughput capacities in Irish poorly productive bedrock aquifers
- Tedd KM, Misstear BDR, Coxon C, et al (2012) Hydrogeological insights from groundwater level hydrographs in SE Ireland. *Q J Eng Geol Hydrogeol* 45:19–30
- Tetko I V., Livingstone DJ, Luik AI (1995) Neural Network Studies. 1. Comparison of Overfitting and Overtraining. *J Chem Inf Comput Sci* 35:826–833. doi: 10.1021/ci00027a006
- Teutschbein C, Seibert J (2012) Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. *J Hydrol*. doi: 10.1016/j.jhydrol.2012.05.052
- Theis C V. (1935) The relation between the lowering of the Piezometric surface and the rate and duration of discharge of a well using groundwater storage. *Eos, Trans Am Geophys Union*. doi: 10.1029/TR016i002p00519
- Thirel G, Andréassian V, Perrin C, et al (2015a) Hydrology under change: an evaluation protocol to investigate how hydrological models deal with changing catchments. *Hydrol Sci J*. doi: 10.1080/02626667.2014.967248
- Thirel G, Andréassian V, Perrin C (2015b) On the need to test hydrological models under changing conditions. *Hydrol Sci J*. doi: 10.1080/02626667.2015.1050027
- Thodsen H (2007) The influence of climate change on stream flow in Danish rivers. *J Hydrol*. doi: 10.1016/j.jhydrol.2006.08.012
- Torrence C, Compo GP (1998) A Practical Guide to Wavelet Analysis. *Bull Am Meteorol Soc*. doi: 10.1175/1520-0477(1998)079<0061:APGTWA>2.0.CO;2
- Tremblay L, Larocque M, Anctil F, Rivard C (2011) Teleconnections and interannual variability in Canadian groundwater levels. *J Hydrol*. doi: 10.1016/j.jhydrol.2011.09.013
- Tularam GA, Ilahee M (2007) Base flow separation using exponential smoothing and its impact on continuous loss estimates. In: *MODSIM07 - Land, Water and Environmental Management: Integrated Systems for Sustainability, Proceedings*
- Turkeltaub T, Kurtzman D, Russak EE, Dahan O (2015) Impact of switching crop type on water and solute fluxes in deep vadose zone. *Water Resour Res*. doi: 10.1002/2015WR017612
- Valens C (1999) A Really Friendly Guide to Wavelets. *Pengantar Kebijak Publik* 7581:87. doi: 10.1093/geronb/51B.4.P234
- van Genuchten MT (1980) A Closed-form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils 1. *Soil Sci Soc Am J*
- Velasco EM, Gurdak JJ, Dickinson JE, et al (2017) Interannual to multidecadal climate forcings on groundwater resources of the U.S. West Coast. *J Hydrol Reg Stud*. doi: 10.1016/j.ejrh.2015.11.018

- Veneziano D, Furcolo P, Iacobellis V (2006) Imperfect scaling of time and space-time rainfall. *J Hydrol*. doi: 10.1016/j.jhydrol.2005.02.044
- Walker D, Parkin G, Schmitter P, et al (2019) Insights From a Multi-Method Recharge Estimation Comparison Study. *Groundwater* 57:245–258. doi: 10.1111/gwat.12801
- Wanner H, Brönnimann S, Casty C, et al (2001) North Atlantic oscillation - Concepts and studies. *Surv Geophys*. doi: 10.1023/A:1014217317898
- Weeks EP (2002) The lisse effect revisited. *Ground Water*. doi: 10.1111/j.1745-6584.2002.tb02552.x
- Whittingham MJ, Stephens PA, Bradbury RB, Freckleton RP (2006) Why do we still use stepwise modelling in ecology and behaviour? *J Anim Ecol*. doi: 10.1111/j.1365-2656.2006.01141.x
- Wilby RL (2005) Uncertainty in water resource model parameters used for climate change impact assessment. *Hydrol Process* 19:3201–3219. doi: 10.1002/hyp.5819
- Wilby RL, Dawson CW, Barrow EM (2002) SDSM—a decision support tool for the assessment of regional climate change impacts. *Environ Model Softw* 17:145–157
- Wilby RL, Dawson CW, Murphy C, et al (2014) The Statistical DownScaling Model-Decision Centric (SDSM-DC): conceptual basis and applications. *Clim Res* 61:259–276
- Wilby RL, Dessai S (2010) Robust adaptation to climate change. *Weather*. doi: 10.1002/wea.543
- Wilby RL, Hay LE, Gutowski WJ, et al (2000) Hydrological responses to dynamically and statistically downscaled climate model output. *Geophys Res Lett* 27:1199–1202
- Wilby RL, Noone S, Murphy C, et al (2016) An evaluation of persistent meteorological drought using a homogeneous Island of Ireland precipitation network. *Int J Climatol*. doi: 10.1002/joc.4523
- Williams NH, Lee M (2010) Ireland at risk—Possible implications for groundwater resources of climate change
- Woldemeskel FM, Sharma A, Sivakumar B, Mehrotra R (2014) A framework to quantify GCM uncertainties for use in impact assessment studies. *J Hydrol* 519:1453–1465
- Woollings T, Hannachi A, Hoskins B (2008) Variability of the North Atlantic eddy-driven jet stream. *Q J R Meteorol Soc*. doi: 10.1002/qj.625
- Wright GR, Fried JJ (1982) Groundwater resources of the Republic of Ireland. Sch" afer
- Wunsch A, Liesch T, Broda S (2018) Forecasting groundwater levels using nonlinear autoregressive networks with exogenous input (NARX). *J Hydrol* 567:743–758. doi: 10.1016/j.jhydrol.2018.01.045
- Wyatt MG, Kravtsov S, Tsonis AA (2012) Atlantic Multidecadal Oscillation and Northern

- Hemisphere's climate variability. *Clim Dyn.* doi: 10.1007/s00382-011-1071-8
- Xiaoying L, Erda L (2005) Performance of the Priestley-Taylor equation in the semiarid climate of North China. *Agric Water Manag.* doi: 10.1016/j.agwat.2004.07.007
- Yoon H, Jun SC, Hyun Y, et al (2011) A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer. *J Hydrol.* doi: 10.1016/j.jhydrol.2010.11.002
- Yu C, Yao Y, Cao G, Zheng C (2015) A field demonstration of groundwater vulnerability assessment using transport modeling and groundwater age modeling, Beijing Plain, China. *Environ Earth Sci.* doi: 10.1007/s12665-014-3769-5
- Zhu L, Wang Y, Fan Q (2014) MODWT-ARMA model for time series prediction. *Appl Math Model.* doi: 10.1016/j.apm.2013.10.002
- Zubiate L, McDermott F, Sweeney C, O'Malley M (2017) Spatial variability in winter NAO–wind speed relationships in western Europe linked to concomitant states of the East Atlantic and Scandinavian patterns. *Q J R Meteorol Soc.* doi: 10.1002/qj.2943

Appendix A

Annual Recharge Estimations from Water Table fluctuation

DRIPSEY

DR1 Shallow	Year	0.01	0.02	0.03	0.04	0.05
		Recharge (mm/y)				
	2010	90	179	269	359	449
	2011	48	96	144	191	239
	2012	58	115	173	231	289
	2013	73	146	219	292	364
	2014	58	117	175	233	291
	2015	55	111	166	222	277

DR1 Shallow 2	Year	Specific Yield				
		0.01	0.02	0.03	0.04	0.05
	Recharge (mm/y)					
	2010	112	225	337	450	562
	2011	80	160	241	321	401
	2012	75	150	225	300	376
	2013	67	135	202	270	337
	2014	64	129	193	257	322
	2015	11	22	33	44	56

DR1 Deep	Year	Specific Yield				
		0.01	0.02	0.03	0.04	0.05
	Recharge (mm/y)					
	2010	112	225	337	450	562
	2011	80	160	241	321	401
	2012	75	150	225	300	376
	2013	67	135	202	270	337
	2014	64	129	193	257	322
	2015	11	22	33	44	56

		Specific Yield				
		0.01	0.02	0.03	0.04	0.05
DR2 Shallow	Year	Recharge (mm/y)				
	2010	160	319	479	639	799
	2011	145	290	435	580	725
	2012	137	275	412	550	687
	2013	184	369	553	738	922
	2014	135	270	404	539	674
	2015	135	270	405	540	675

		Specific Yield				
		0.01	0.02	0.03	0.04	0.05
DR2 Deep	Year	Recharge (mm/y)				
	2010	163	327	490	653	817
	2011	172	345	517	689	862
	2012	65	130	195	261	326
	2013	0	0	0	0	0
	2014	5	11	16	22	27
	2015	194	388	582	776	970

		Specific Yield				
		0.01	0.02	0.03	0.04	0.05
DR3 Subsoil	Year	Recharge (mm/y)				
	2010	67	134	201	268	335
	2011	81	163	244	326	407
	2012	66	132	197	263	329
	2013	65	131	196	262	327
	2014	85	170	255	341	426
	2015	87	175	262	349	436

MATTOCK

		Specific Yield				
		0.01	0.02	0.03	0.04	0.05
MK1 Subsoil	Year	Recharge (mm/y)				
	2010	56	113	169	226	282
	2011	49	98	147	197	246
	2012	106	211	317	422	528
	2013	64	127	191	255	318
	2014	68	136	204	272	340
	2015	27	54	81	108	135

		Specific Yield				
		0.01	0.02	0.03	0.04	0.05
MK1 Shallow	Year	Recharge (mm/y)				
	2010	60	120	179	239	299
	2011	45	90	135	180	225
	2012	68	136	204	272	340
	2013	63	127	190	254	317
	2014	71	142	213	284	355
	2015	47	94	141	188	235

		Specific Yield				
		0.01	0.02	0.03	0.04	0.05
MK2 Deep	Year	Recharge (mm/y)				
	2010	22	45	67	90	112
	2011	29	59	88	117	147
	2012	31	61	92	123	153
	2013	43	86	129	172	215
	2014	31	61	92	122	153
	2015	39	77	116	154	193

		Specific Yield				
		0.01	0.02	0.03	0.04	0.05
MK3 Subsoil	Year	Recharge (mm/y)				
	2010	40	80	120	159	199
	2011	32	64	96	128	160
	2012	53	106	159	212	265
	2013	48	97	145	194	242
	2014	60	120	180	239	299
	2015	55	110	165	221	276

		Specific Yield				
		0.01	0.02	0.03	0.04	0.05
MK3 Shallow	Year	Recharge (mm/y)				
	2010	61	121	182	243	303
	2011	83	165	248	330	413
	2012	171	342	513	684	855
	2013	38	75	113	151	188
	2014	28	55	83	110	138
	2015	37	73	110	147	183

NAM parametrization

parameter	Mattock	Dripsey
$U_{\max}$	20	14
$L_{\max}$	400	120
C_{QOF}	0.645	0.68
CKIF	500	100
CK_{12}	35	22
TOF	0.6	0.754
TIF	0.6	0.9
TG	0.85	0.5
CKBF	1000	1569
CQ_{low}	500	81.1
CKI_{ow}	2025.25	1184.65

Specific Yield estimations from Recharge

DRIPSEY

		2010	2011	2012	2013	2014	2015
Recharge 200	DR1 Shallow	0.022	0.037	0.030	0.025	0.034	0.031
	DR1 Shallow2	0.018	0.024	0.026	0.029	0.032	0.163
	DR1 deep	0.018	0.024	0.026	0.029	0.033	0.163
	DR2 shallow	0.012	0.012	0.014	0.010	0.01	0.014
	DR2 deep	0.012	0.011	0.030	0	0.530	0.010
	DR3 shallow	0.045	0.041	0.046	0.039	0.043	0.040

		2010	2011	2012	2013	2014	2015
Recharge 250	DR1 Shallow	0.035	0.0523	0.043	0.034	0.060	0.048
	DR1 Shallow2	0.022	0.031	0.033	0.037	0.038	0.022
	DR1 deep	0.022	0.031	0.033	0.037	0.038	0.022
	DR2 shallow	0.015	0.017	0.018	0.013	0.018	0.018
	DR2 deep	0.015	0.014	0.038	0.030	0.046	0.013
	DR3 shallow	0.057	0.051	0.057	0.048	0.054	0.050

		2010	2011	2012	2013	2014	2015
Recharge 300	DR1 Shallow	0.04	0.062	0.050	0.041	0.070	0.057
	DR1 Shallow2	0.023	0.037	0.040	0.044	0.046	0.269
	DR1 deep	0.023	0.037	0.040	0.044	0.046	0.269
	DR2 shallow	0.0188	0.020	0.022	0.016	0.023	0.022
	DR2 deep	0.0186	0.017	0.046	0.040	0.557	0.015
	DR3 shallow	0.0686	0.061	0.069	0.058	0.064	0.060

MATTOCK

		2010	2011	2012	2013	2014	2015
Recharge 70	MK1 Subsoil	0.012	0.014	0.006	0.011	0.010	0.026
	MK1 Shallow	0.012	0.016	0.010	0.011	0.010	0.015
	MK1 deep	0.023	0.012	0.012	0.014	0.020	0.016
	MK2 deep	0.031	0.024	0.023	0.016	0.023	0.018
	MK3 subsoil	0.018	0.022	0.013	0.015	0.012	0.013

		2010	2011	2012	2013	2014	2015
Recharge 100	MK1 Subsoil	0.018	0.021	0.010	0.016	0.015	0.038
	MK1 Shallow	0.017	0.021	0.015	0.016	0.014	0.021
	MK1 deep	0.033	0.017	0.018	0.020	0.028	0.023
	MK2 deep	0.045	0.034	0.033	0.023	0.033	0.026
	MK3 subsoil	0.025	0.031	0.019	0.021	0.017	0.018

		2010	2011	2012	2013	2014	2015
Recharge 170	MK1 Subsoil	0.030	0.035	0.016	0.027	0.025	0.063
	MK1 Shallow	0.028	0.038	0.025	0.027	0.024	0.036
	MK1 deep	0.056	0.030	0.030	0.034	0.048	0.039
	MK2 deep	0.076	0.058	0.055	0.040	0.056	0.044
	MK3 subsoil	0.043	0.053	0.032	0.035	0.028	0.031

Appendix B

Continuous Wavelet Transforms of the Teleconnection Indices

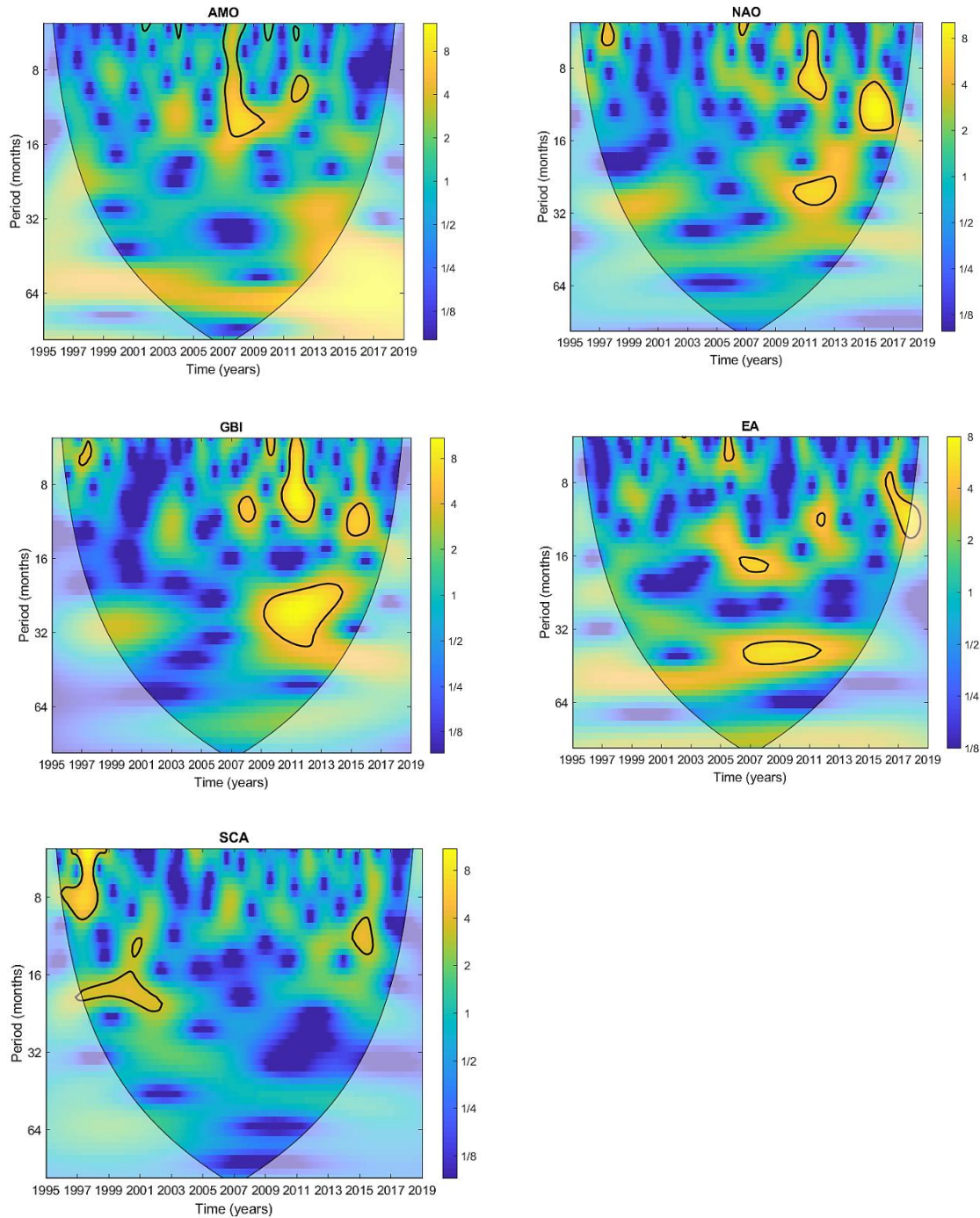


Figure B.1: Scalograms of the Teleconnection patterns considered (from right to left and top to bottom): Atlantic Multidecadal Oscillation, North Atlantic Oscillation, Greenland Blocking Index, East Atlantic Pattern and Scandinavian Pattern.

Appendix C

Net change of the variables calculated from NAM:

MATTOCK

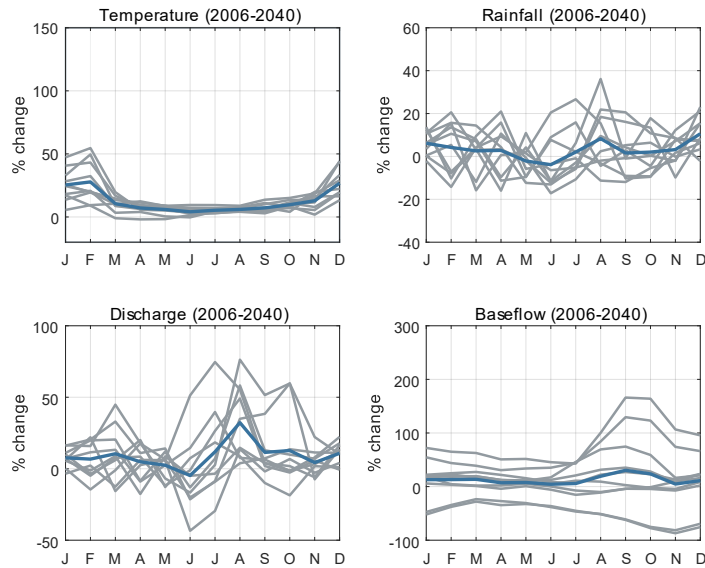


Figure C.1: Net Change if the hydrological variables during the period P1 (2006-2040) for all the projections (grey) and the corresponding mean (blue) for the Mattock catchment.

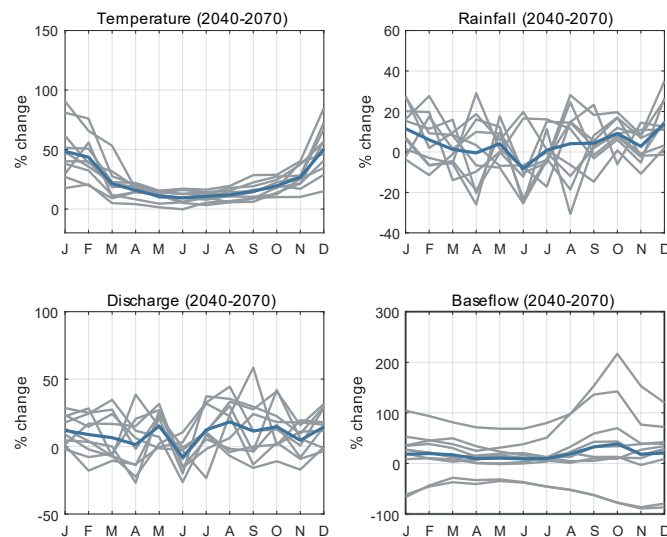


Figure C.2: Net Change if the hydrological variables during the period P2 (2040-2070) for all the projections (grey) and the corresponding mean (blue) for the Mattock catchment

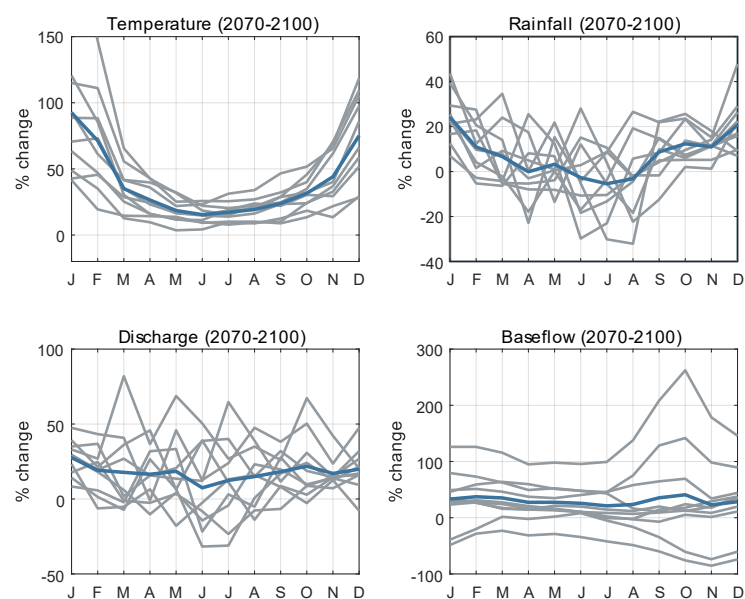


Figure C.3: Net Change if the hydrological variables during the period P3 (2070-2100) for all the projections (grey) and the corresponding mean (blue) for the Mattock catchment

DRIPSEY

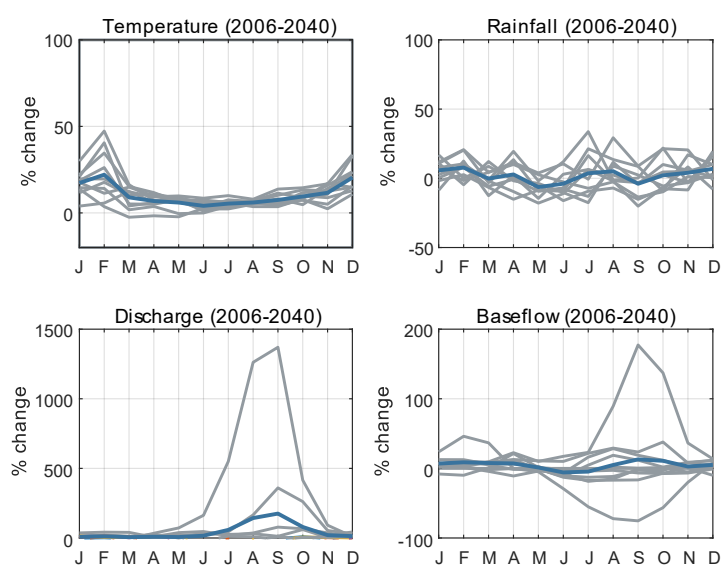


Figure C.4: Net Change if the hydrological variables during the period P1 (2006-2040) for all the projections (grey) and the corresponding mean (blue) for the Dripsey catchment

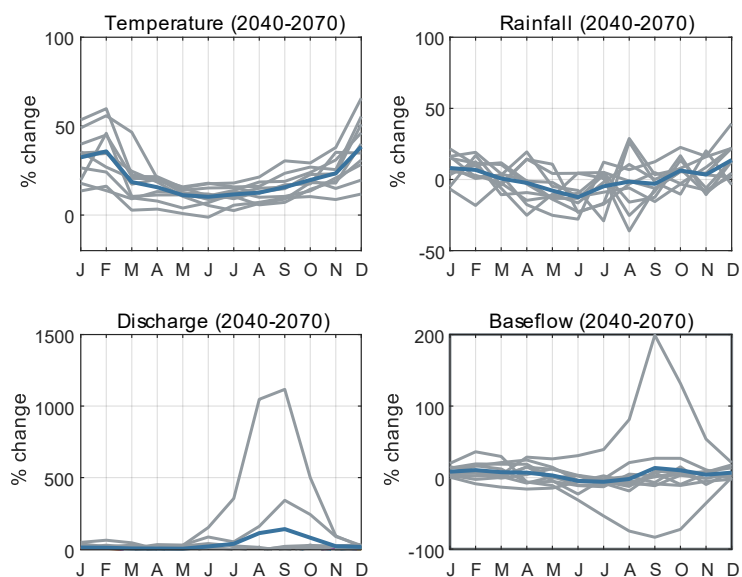


Figure C.5: Net Change if the hydrological variables during the period P2 (2040-2070) for all the projections (grey) and the corresponding mean (blue) for the Dripsey catchment

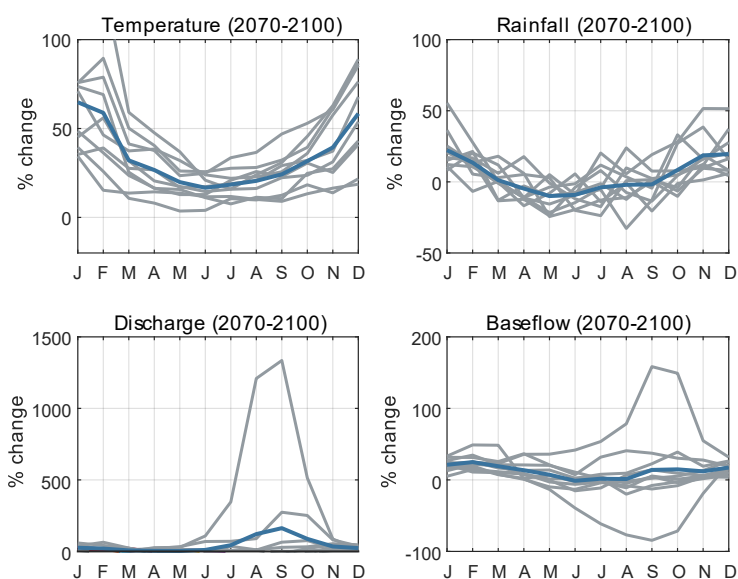


Figure C.6: Net Change if the hydrological variables during the period P3 (2070-2100) for all the projections (grey) and the corresponding mean (blue) for the Dripsey catchment

Climate projections used as an input for the WT-NARX model for the Dripsey:

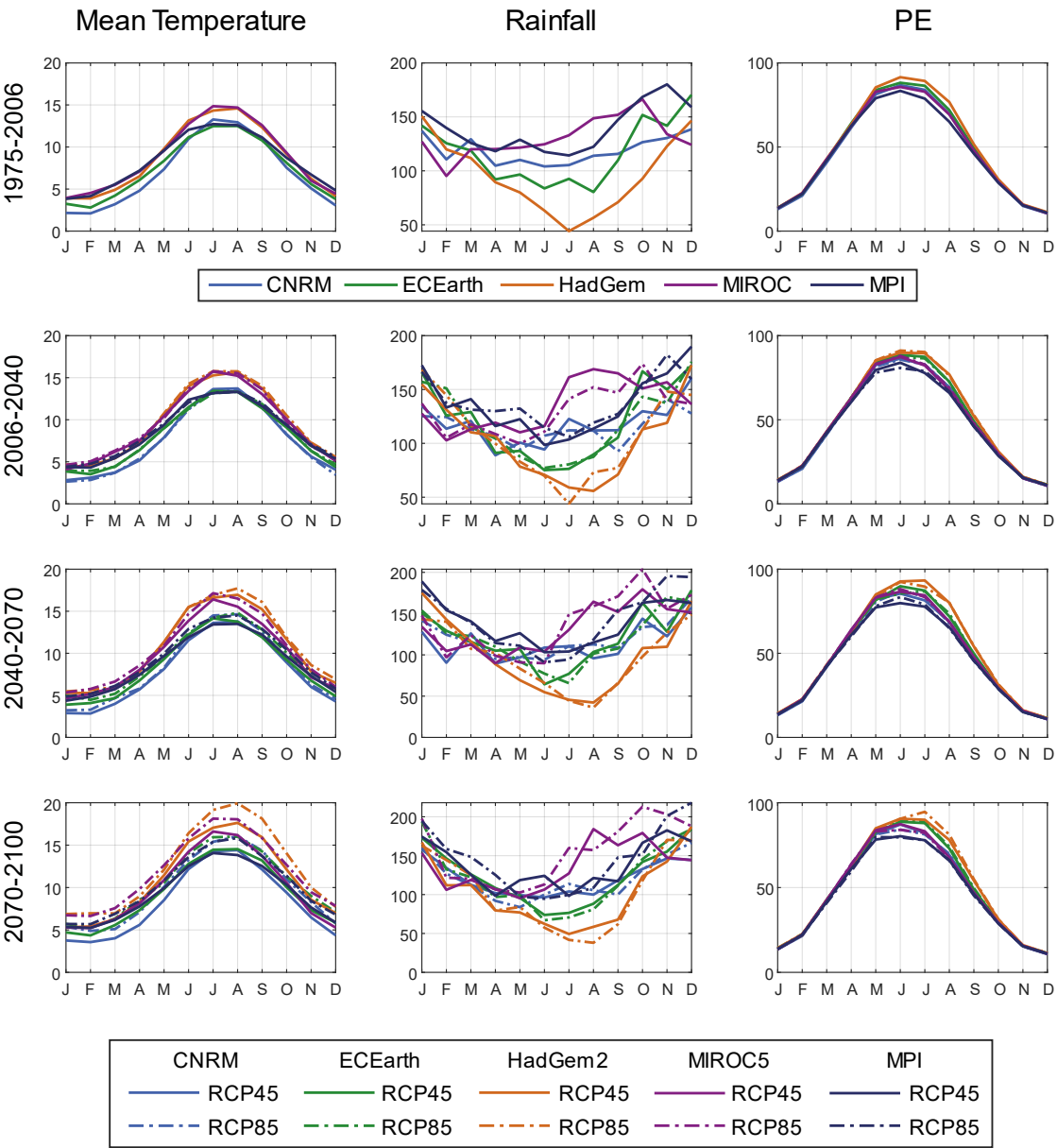


Figure C.7: Annual cycles of the climate projections for the historical period (first row) and future periods of the WT-NARX model inputs for the Dripsey catchment.

